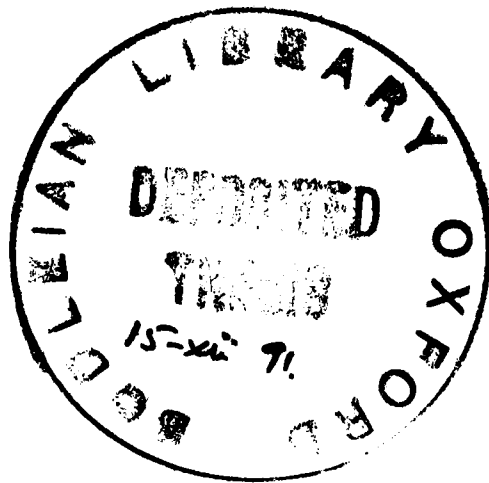




CONVENTIONS AND THE STOCK MARKET GAME

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## ABSTRACT

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Forecasting stock price movements is a notoriously difficult job. Were it not so, it would be easy to get richer. In this case, however, nobody would get poorer. But if nobody gets poorer, nobody will get richer. There are two ways to get out of this vicious circle. The first, and the more well-trodden, is the Efficient Market Theory (EMT), or: Everybody Understands Everything. The second is the Casino Market Theory (CMT), or: Nobody Understands Anything. This work is an attempt to bridge the gap between these two theories.

In the first chapter the EMT is analysed in its fundamental constituents, while Chapter 2 contains a discussion of several empirical tests of the theory. Chapter 3 extends the EMT to incorporate variable risk premia and rational speculative bubbles and Chapter 4 presents the available empirical evidence on the extended model.

The line of research based on the EMT paradigm is abandoned in Chapter 5, where the central principle of the EMT - the assumption of homogeneous investors with common priors - is investigated and challenged. The basis is there laid for an alternative view of the stock market game, which emphasises the conventional nature of investors' beliefs about future returns and is consistent with the view that stock market prices do not only reflect the fundamental value of underlying companies. In Chapter 6, the hypothesis that non fundamental information (in particular, past information) may have an influence on current stock prices is evaluated against monthly data relative to the US, UK, Japanese and Italian stock markets. Contrary to popular wisdom, we find that past information has a significant effect on current stock returns. Our evidence indicates that, as Keynes suggested in the General Theory, conventional beliefs play a crucial role in the stock market game.

## ACKNOWLEDGEMENTS

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Spesso in simili circostanze, l'annunzio di una cosa la fa essere.

(A. Manzoni)

## CHAPTER 1

### STOCK MARKET EFFICIENCY: REVIEW-CUM-CLARIFICATIONS

#### I. Introduction.

The spectacular fall in world stock prices which occurred in October 1987 has given economists a new opportunity to question the ability of traditional theories of stock market behaviour to account for the observed pattern of stock price movements. After Black Monday few in the profession have been spared the embarrassing question: Did you predict the crash? After all, people think that economists should be able not only to provide ex-post explanations of economic phenomena, but also to predict them. It is not easy to dispel doubts about the relevance of Economic Theory by mentioning the existence of precise economic arguments for believing that Black Monday was inherently unpredictable. Some might have tried to quote Samuelson and say that if a theory to predict the crash was available, economists would be richer than they actually are. But again, this

hardly sounds too convincing. If monkeys can't play Bach, it doesn't necessarily follow that Bach cannot be played.

It is unquestionably true, however, that forecasting stock price movements, just like playing Bach, is not at all an easy job. In this respect, laymen cannot disagree with economists, although it will not come as too much of a surprise to them to learn that economists do disagree among themselves as to the causes of their poor chances as speculators. On one side, in fact, one finds a nicely developed and quite substantial body of theoretical and empirical work which maintains that stock market participants have such a complete and detailed knowledge of the market mechanisms that competition among them automatically ensures that all available information is reflected in stock prices and no single agent can systematically beat the others and make steady profits out of a given rule for buying and selling shares. This view, known as the Efficient Market Theory (henceforth EMT), has reached a well-respected status in the past twenty years, and is still the dominant view among economists today. On the other side of the spectrum, however, the discerning observer will notice another much more disorganised and fluid set of theories, which loosely maintain that everybody's (both economists' and investors') knowledge of the market is so limited and imperfect, compared to the complexity of the mechanisms involved, that it is very difficult, although not impossible in principle, to discover operational rules which could be used to predict future

price movements. The idea that the stock market game is a complicated and hazardous activity was put forward by Keynes in Chapter 12 of the General Theory. His view of the stock market as a casino, potentially able to inject dangerous instability into the economy, is well-known, although today rarely subscribed to by economists, given the predominance of the EMT. The view is much more popular among market participants, who indeed spend much time and effort in trying to anticipate the market, using a whole lot of variegated and often fanciful devices. We shall call this second view the Casino Market Theory (hereafter CMT).

This study can be viewed as an attempt to bridge the gap between the EMT and the CMT. The current debate about stock market behaviour is often cast in terms of an opposition between rational and non rational agents. On the one hand, advocates of the EMT find it natural to argue that, as stock markets are populated by numerous rational and profit-seeking individuals, stock prices should reflect all available information. However, they often neglect to specify what information should be reflected into prices. If it is only fundamental information (i.e. information about the fundamental value of the underlying firms), then it becomes quite hard for them to explain a large number of price changes, which are either patently unrelated to any new piece of such information or are clearly excessively large to be explained on such grounds (the October 1987 crash being only the most conspicuous example). But if prices also

reflect non fundamental information, then the main tenet of the EMT breaks down. Those who, on the other hand, believe that stock prices reflect other things beyond fundamental information are inclined to claim that stock market participants are subject to a variety of fads and manias which have very little to do with rationality. They omit to explain, however, why the otherwise well-respected rationality axiom should fail to apply precisely where it might be thought to be more forcefully in place, i.e. among bright, educated and well-informed individuals.

We regard the opposition between these two views as a major obstacle to a better understanding of stock market behaviour. Our claim that, far from reflecting individual irrationality, stock price reaction to non fundamental information is entirely consistent with rationality, even though the interaction of individually rational agents may produce outcomes which in some sense can be regarded as irrational as a whole.

We start off in the present chapter with a review of the EMT, focusing on the analysis of its constituent hypotheses and their implications. In particular, the role played in this context by the Rational Expectations hypothesis will be carefully scrutinised. After a general introduction to the EMT, some rather important points of terminological clarification will be discussed.

## II. The Fundamental Valuation Model.

The well-known proposition according to which the expectations of rational economic agents are equal to the mathematical expectation drawn from the true economic model of reality is at the core of the Rational Expectations Hypothesis. This proposition can be challenged and defended on several grounds, but it seems plausible to regard stock markets as the closest approximation to the ideal-type set-up of Rational Expectations models. This is true on many accounts, among which informational assumptions hold a prominent place. Stock market investors exchange goods (equity shares) at the same time and in the same place, at continuously quoted prices; they carefully record and assess new information as it becomes available; their information processing is relatively fast, allowing for no substantial lag in the adjustment towards market-clearing, which can be assumed to hold at each point in time.

Hence stock markets provide one of the most straightforward tests for an appraisal of the Rational Expectations Hypothesis. Indeed, the latter is the fundamental prerequisite of the Efficient Market Theory (EMT), which constitutes the point of departure of the entire modern theory of finance.<sup>1</sup> Our first aim is to analyse the

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1. It is interesting to note that the connection between the EMT and Rational Expectations can be traced back to well before the same expression 'Rational Expectations' had been coined. See Bachelier (1900) in Cootner (1964).

fundamental constituents of the EMT and to clarify some relevant issues thereabouts.

A financial market is said to be informationally efficient if prices always 'fully reflect' available information.<sup>2</sup> Define:

$$r_t = (P_{t+1} - P_t + D_{t+1}) / P_t = [(P_{t+1} + D_{t+1}) / P_t] - 1 \quad (1.1)$$

as the one-period rate of return on a given stock of equity capital held from the beginning until the end of time  $t$ . Assuming no taxes, no transaction costs and no short sale restrictions,  $r_t$  is equal to the sum of a capital gain (or loss)  $(P_{t+1} - P_t) / P_t$  - where  $P_t$  is the market price of the share at the beginning of time  $t$  - and a dividend yield  $D_{t+1} / P_t$ , where  $D_{t+1}$  is the dividend paid at the end of time  $t$  (i.e. the beginning of time  $t+1$ ). Throughout the study we shall refer to real prices and dividends (hence real returns), which are defined as the corresponding nominal series divided by a price index in order to correct for inflation.<sup>3</sup> The stock can be assumed to represent a single share or the entire market portfolio. As this study is concerned with aggregate stock market behaviour, we shall henceforth refer to the latter case.

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2. This traditional definition of market efficiency is due to Fama (1970). See also Fama (1976). Both contain a detailed exposition of the earlier versions of the EMT, together with a discussion of empirical testing.

3. Of course dividing prices and dividends by a price index is equivalent to dividing  $(1+r_t)$  by one plus the rate of inflation.

The variable  $r_t$  is by definition the rate of return earned by an investor who buys the share at the beginning of period  $t$  and sells it at the end. Hence  $r_t$  is a random variable at the beginning of the period, and we denote its conditional expectation as  $E_t r_t = \lambda_t$ , where  $E_t = E(\cdot | \Phi_t)$  is the expectation operator conditional on the information set  $\Phi_t$  available at the beginning of time  $t$ . Notice that, by definition:

$$E_t(r_t - \lambda_t) = 0 \quad (1.2)$$

i.e. the random sequence  $\{\epsilon_t\} = \{r_t - \lambda_t\}$  is a martingale difference relative to the increasing sequence of  $\sigma$ -fields  $\{\Phi_t\}$  (provided that  $r_t$  has a finite unconditional mean).<sup>4</sup> A martingale difference is a random sequence with zero conditional mean, whose terms are serially uncorrelated and orthogonal to the realisations of the conditioning variables in the information set. Clearly, (1.2) is a general property of any finite-mean random sequence: the deviation of any such sequence from its conditional mean is a martingale difference. It follows that - provided  $r_t$  has a finite unconditional mean - (1.2) holds by definition and cannot be attached any theoretical (i.e. behavioural) significance. This is an important point to bear in mind in order to understand the role played in the EMT by the Rational Expectations Hypothesis. In fact, only after assuming that investors

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4. See e.g. Spanos (1986, p. 146).

hold homogeneous rational expectations can an arbitrage argument be employed in order to interpret  $\lambda_t$  - which will thus also denote investors' subjective expectations on  $r_t$  conditional on  $\Phi_t$  - as the equilibrium return which investors expect to obtain over one holding period. Accordingly,  $\epsilon_t$  can be interpreted as the excess return over the equilibrium  $\lambda_t$  and equation (1.2) as showing that the excess return expected by rational investors at each  $t$  is equal to zero. Were this not the case - thus the EMT argument runs - investors could utilise information available at  $t$  to generate a non-zero expected excess return. As investors are all equally rational, however, each one of them would be able to do so. But, for this very reason, no one actually could, as most stock market transactions are zero-sum games in which somebody's gain has to be somebody else's loss. In the EMT jargon, one says that no single investor can beat the market (i.e. other investors) using trading rules based on available information. Hence a simple Buy-And-Hold strategy is sufficient to generate the equilibrium expected rate of return  $\lambda_t$ .

In the EMT literature (1.2) is known as the 'fair game' property of stock returns and the sequence  $\{\epsilon_t\}$  is said to be a 'fair game' relative to the information set  $\Phi_t$ . Later on in chapter 5 we shall expand on this property and analyse its content in more detail. But for the moment we confine ourselves to our exposition of the EMT. Notice then that the EMT arbitrage argument based on Rational Expectations allows us to determine an equilibrium price  $P_t$  from

equation (1.2). In fact, taking expectations in (1.1) and rearranging we obtain:

$$P_t = (1+\lambda_t)^{-1} E_t(P_{t+1} + D_{t+1}) \quad (1.3)$$

The argument is the following. Imagine that the price is lower than  $P_t$ . Then  $E_t r_t$  would be greater than  $\lambda_t$ , i.e. investors would expect a positive excess return and would thus want to buy the share at  $t$ , thereby bidding the price up to the point in which (1.3) holds. Similarly, a price higher than  $P_t$  would imply a negative expected excess return and a bidding down of the price towards  $P_t$ .

Notice then that equation (1.3) - suitably interpreted - is a first-order stochastic difference equation, whose general solution has the form<sup>5</sup>

$$\begin{aligned} P_t &= \sum_{i=1}^{\infty} E_t \left[ \prod_{j=1}^i (1+\lambda_{t+j-1})^{-1} \right] D_{t+i} + \prod_{i=0}^{t-1} (1+\lambda_i) B_t \\ &= P_t^F + B_t^* \end{aligned} \quad (1.4)$$

provided that  $B_t$  is a martingale process, i.e.  $E_t B_{t+1} = B_t$ . This solution has two components. The first, which we call  $P_t^F$ , can be obtained by recursive forward substitution in (1.3), provided that:

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5. See, e.g., Pesaran (1987), Chapter 5.

$$\lim_{i \rightarrow \infty} E_t \left[ \prod_{j=1}^i (1 + \lambda_{t+j-1})^{-1} \right] P_{t+i} = 0 \quad (1.5)$$

This first component is equal to the infinite discounted sum of rationally expected dividends, where the discount rate is the expected rate of return  $\lambda_t$ . Therefore, if  $B_t$  (hence  $B_t^*$ ) is zero in (1.4) and  $P_t = P_t^F$ , the price is said to reflect the 'market fundamentals' about the value of the stock. At each point in time,  $P_t$  reflects all available information about the 'fundamental' or 'intrinsic' value of the firm - as represented by the discounted stream of its future dividend payments. Therefore, when  $B_t = 0$ , we call (1.4) the Fundamental Valuation Model (henceforth FVM). Stock markets in which prices follow the FVM are informationally efficient because  $P_t$  accurately reflects all available information on the fundamental value of firms and is therefore the most reliable indicator for the optimal allocation of capital. Notice that the FVM shares the same 'fair game' property of the EMT, from which it originates. Since  $P_t$  reflects all available information in  $\{\Phi_t\}$ , the latter cannot be utilised to generate future price forecasts. Only the arrival of new information after  $t$  will be able to cause a revision of investors' expectations, hence a change in  $P_t$ . However, while the EMT leaves the information content of  $\Phi_t$  unspecified, its FVM version requires that  $\Phi_t$  contain only information about the discounted sum of future

dividend payments, as only this kind of information can produce changes in  $P_t$ . But more about this in Chapter 5.

For the current purposes, notice that, when  $B_t$  is not zero, equation (1.4) contains a second component,  $B_t^*$ , whose factor  $B_t$  is a martingale process with no intrinsic relation to fundamental values. In this case stock prices do not only reflect market fundamentals but are also driven by  $B_t^*$ . Notice also that, since  $E_t B_{t+1}^* = (1+\lambda_t) B_t^*$ , the process  $B_t^*$ , and consequently  $P_t$ , are expected to follow an explosive path. The variable  $B_t^*$  is referred to as a 'rational bubble'. The term 'rational' relates to the fact that, although  $P_t$  in (1.4) does not reflect fundamentals when a bubble is present, it still is a solution to the difference equation (1.3). Hence, it is consistent with the assumptions required to obtain (1.3), including the Rational Expectations Hypothesis.<sup>6</sup> As long as the event of boundless growth has positive probability, the rational bubble  $B_t^*$  is ruled out by imposing the transversality condition (1.5), which prevents the stock price from growing arbitrarily large in the infinite future. In fact:

$$\lim_{i \rightarrow \infty} E_t \left[ \prod_{j=1}^i (1+\lambda_{t+j-1})^{-1} \right] P_{t+i} = \lim_{i \rightarrow \infty} E_t \left[ \prod_{j=1}^i (1+\lambda_{t+j-1})^{-1} \right] P_{t+i}^F$$

$$+ \prod_{i=0}^{t-1} (1+\lambda_i) B_t = 0$$

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6. Blanchard (1979) and Blanchard and Watson (1982) first pointed out the possibility of rational bubbles in the context of the FVM.

implies  $B_t=0$ , since  $\lim E_t[\Pi(1+\lambda_{t+j-1})^{-1}]P_{t+i}^F=0$  by definition.

In the sequel, we shall impose (1.5) as to eliminate  $B_t$  and adopt the FVM as our model of stock market behaviour. This corresponds to the prevailing practice in the finance literature, where the FVM represents the standard model of market efficiency. We shall return to rational bubbles in Chapters 3 and 4, where we shall see that the existence of such bubbles can be ruled out on strictly theoretical as well as empirical grounds.

A second widespread practice in the literature is to assume that the equilibrium rate of return  $\lambda_t$  is a positive constant:

$$\lambda_t = r > 0 \quad (1.6)$$

This assumption simplifies equations (1.3)-(1.5) into:

$$P_t = (1+r)^{-1} E_t(P_{t+1} + D_{t+1}) \quad (1.7)$$

$$P_t = \sum_{i=1}^{\infty} (1+r)^{-i} E_t D_{t+i} + (1+r)^t B_t \quad (1.8)$$

$$\lim_{i \rightarrow \infty} (1+r)^{-i} E_t P_{t+i} = 0 \quad (1.9)$$

The rationale behind (1.6) will also be analysed in Chapter 3. Here notice that, further assuming that dividends grow at a constant rate  $g$ , and that  $g$  is smaller than the discount rate  $r$ , (1.8) reduces to:

$$P_t = D_t / (r - g) \quad (1.10)$$

which is commonly known in finance textbooks as the Gordon-Shapiro model.

Let us at this stage summarise the basic hypotheses of the FVM: 1) Investors are identical and receive the same information; 2) Their expectations are rational; 3) The transversality condition holds and rules out rational bubbles; 4) The expected rate of return is constant. In the following chapters we are going to discuss each of the four hypotheses and investigate their specific role within the EMT. A significant difference between the first and the second couple of hypotheses can however be noticed here. While the latter are properties of the FVM, and can be relaxed without impairing the basic tenets of the EMT,<sup>7</sup> the former refer to the rationality of stock market investors and, as such, are essential constituents of the EMT.

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7. Of course, in the presence of rational bubbles stock prices will not at each point in time reflect market fundamentals. However, the explosive nature of such bubbles implies that the concept is relevant only if bubbles 'come and go' intermittently, thereby allowing for a weaker - but intrinsically equivalent - form of efficiency.

Rational bubbles and expected discount rates will be analysed in Chapter 3, while Chapter 5 will deal with the more fundamental questions of rationality and homogeneity. In Chapter 2 we shall instead concentrate on the empirical tests of the FVM. Before doing so, however, some terminological clarifications are in order.

### III. Martingales and random walks.

We have seen in the previous section that the 'fair game' property of stock market returns asserts that the excess return  $\{\epsilon_t\}$  follows a martingale difference relative to the sequence of  $\Phi_t$ . The term 'martingale' is indeed a recurring one in the EMT literature, where it is commonly employed to defend the EMT main claim about the inherent unpredictability of stock price changes. An unhealthy degree of confusion is however generated each time the term is inappropriately used to suggest that in an efficient stock market the sequence of price levels should itself follow a martingale.

Remember that a stochastic process  $\{P_t\}$  follows a martingale relative to the increasing sequence of  $\sigma$ -fields  $\{\Phi_t\}$  if:<sup>8</sup> i)  $E|P_t| < \infty$  for all  $t$  ii)  $E(P_{t+1}|\Phi_t) = E_t P_{t+1} = P_t$  for all  $t$ . Three main features of this definition should be noted. First, the unconditional mean of a martingale is constant, since  $E(E_t P_{t+1}) = E(P_{t+1}) = E(P_t)$  for all  $t$ . Second, the sequence  $\{P_t\}$  does not need to be independent or

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8. See e.g. Grimmett and Stirzaker (1982).

identically distributed. It follows that a random walk  $P_{t+1}=P_t+v_{t+1}$  (where  $v_{t+1}$  is white noise, i.e. an independent and identically distributed disturbance with zero mean and constant variance), is a martingale - since  $E_t P_{t+1}=P_t$  - but the reverse is not necessarily true. Third, in a martingale the conditional expectation at time  $t$  of next period's random variable  $P_{t+1}$  is equal to the observable realisation of the variable at  $t$ .

It was this latter feature of the martingale process which first prompted Samuelson (1965,1973) and Mandelbrot<sup>9</sup> (1966) to use martingales to explain the behaviour of prices in efficient financial markets. Their theoretical work was preceded, and indeed motivated, by a body of empirical research on the autocorrelation of price differences. In particular, Kendall (1953) analysed the time series properties of different stock and other speculative price series and found little evidence of autocorrelation in their weekly first differences. He concluded that "prediction in such series, from internal behaviour alone, is subject to a wide margin of error and the best estimate of the change in price between now and next week is that there is no change." (p.18). Kendall was the first to base this result on an comprehensive empirical analysis, but the same conclusion had been reached much earlier by Bachelier (1900), whose 'fundamental principle' for the behaviour of speculative prices postulated that expected profits from speculation are equal to zero.

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9. Yes, he is the same fellow who later invented fractals.

Although Kendall felt that economists would "doubtlessly resist such conclusion very strongly", indeed nothing of the kind happened, and the Samuelson-Mandelbrot final rationalisation of Kendall's findings was only the culmination of a number of studies, all pointing towards the same direction.<sup>10</sup> Samuelson and Mandelbrot simply noticed that (1.2) can be written as:

$$E_t(P_{t+1} + D_{t+1}) = (1 + \lambda_t)P_t \quad (1.11)$$

Equation (1.11) shows that, under Rational Expectations, stock prices, adjusted for dividends and discounting, follow a first-order Markov process: conditional on the present price, the future price does not depend on the past. We call this the 'martingale' or 'random walk' property of stock prices because, in practice,  $P_{t+1}$  and  $P_t$  are almost equal to  $P_{t+1} + D_{t+1}$  and  $(1 + \lambda_t)P_t$  respectively. It must be noticed, however, that equation (1.11) does not say that stock prices themselves follow a martingale, since this would only be true if the price sequence had a constant population mean and:

$$E_t D_{t+1} / P_t = E_t D_{t+1} / E_t P_{t+1} = \lambda_t \quad (1.12)$$

which in turn implies  $E_t D_{t+i} = \lambda_t P_t = \lambda_t E_t P_{t+1}$  for all  $i$ . The reason is clear. If  $E_t P_{t+1} = P_t$  the expected capital gain component of return is

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10. Cootner (1964) contains a summary of these earlier studies.

by definition equal to zero. Hence the expected return coincides with the expected dividend yield.

Adding restriction (1.12) to (1.11) makes the Samuelson-Mandelbrot formulation of the EMT coincide with the conclusions of Bachelier and Kendall. In our terminology, the latter would say that, if rational market participants process information in an efficient manner and react immediately to news, current prices should reflect all available information and only unanticipated information should be able to produce a change in the price from its current level. Therefore, the best estimate of next period price, given current information, is the current price, which precisely says that the price sequence is a martingale relative to current information. Without restriction (1.12), however, stock prices themselves do not follow a martingale. As we know, the process possessing the martingale property is rather  $\{\epsilon_t\}$ , which follows a martingale difference relative to  $\{\Phi_t\}$ .

Indeed, since in practice  $P_{t+1}$  and  $P_t$  are very similar to  $(P_{t+1}+D_{t+1})$  and  $(1+\lambda_t)P_t$ , there is a sense in saying that prices 'almost' follow a martingale. Moreover, since dividends are distributed discontinuously by firms (usually once or twice a year), equation (1.11) becomes  $E_t P_{t+1} = (1+\lambda_t)P_t$  for shorter (e.g. weekly) time spans. This implies that the expected rate of growth of  $P_t$  - i.e. the expected capital gain - is equal to  $\lambda_t$ , which would be

approximately true if  $P_t$  followed a geometric random walk with a variable drift:

$$\ln P_{t+1} = \lambda_t + \ln P_t + \zeta_{t+1} \quad (1.13)$$

The Bachelier-Kendall conclusion would in this case obtain if  $\lambda_t=0$ , i.e. the best estimate of (the log of) next period price is (the log of) the current price. However, if  $\lambda_t \neq 0$ , the unconditional mean of  $\ln P_t$  would be undefined (infinite in the limit), and this would be inconsistent with the definition of martingales.

In any case, it is important to notice that the FVM establishes a link between the generating processes of dividends and prices, with the latter logically dependent on the former. Assume, for instance, that dividends follow a first-order autoregressive process:

$$D_{t+1} = \mu + \rho D_t + \xi_{t+1} \quad (1.14)$$

where  $\mu$  is a constant term,  $|\rho| < 1$  and  $\xi_t$  is a white noise process with zero mean, variance  $\sigma^2$  and no serial correlation. It follows that  $E_t D_{t+1} = \mu + \rho D_t$  and, by recursive backward substitution:

$$E_t D_{t+i} = \mu + E_t D_{t+i-1} = \mu[(1-\rho^i)/(1-\rho)] + \rho D_t$$

Assume also that prices are determined by the FVM, with  $\lambda_t=r$  for simplicity. Then, substituting in (1.8) (with  $B_t=0$ ) we obtain:

$$\begin{aligned} P_t &= \sum_{i=1}^{\infty} (1+r)^{-i} E_t D_{t+i} = \mu/(1-\rho) \sum_{i=1}^{\infty} [(1-\rho)/(1+r)]^i + D_t \sum_{i=1}^{\infty} [\rho/(1+r)]^i \\ &= a + bD_t \end{aligned} \quad (1.15)$$

where  $a=[\mu(1+r)]/[r(1+r-\rho)]$  and  $b=[\rho/(1+r-\rho)]$ . (Notice that  $a$  and  $b$  would be variables in the general case (1.4)). Equation (1.15) is a mapping from the information set  $\{\Phi_t\}=\{D_t\}$  into  $P_t$ . The fact that  $\{\Phi_t\}$  and (1.15) only include current dividends depends on the assumed autoregressive form for  $D_t$ . In this case, in fact, current dividends summarise all the information needed to forecast future dividends, and hence the current price. The assumption is, of course, incredibly restrictive, and we adopt it here only for expositional purposes.<sup>11</sup> We imagine that investors know the law of motion of  $D_t$ , given by (1.14), and that they assume (1.15) to be the pricing function giving the law of motion of  $P_t$ . Then equation (1.11) can be seen as a mapping from the perceived price into the actual price, and a Rational Expectations Equilibrium is defined as a fixed point on this mapping, i.e. the point at which the perceived and the actual price coincide. The link between the generating processes of dividends and

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11. In fact, the assumption plays an important role in the context of the consumption-based Capital Asset Pricing Model, as developed, e.g., by Lucas (1978). More about the CCAPM in Chapter 3.

prices can then be obtained by substituting for  $D_t$  from (1.14) into the pricing function (1.15):

$$P_{t+1} = \mu/r + \rho P_t + b\xi_{t+1} \quad (1.16)$$

Equation (1.16) shows that, if dividends follow an AR1 process, prices will also follow an AR1 process, with the same autoregressive parameter  $\rho$ , and that this is true precisely because the stock market is efficient, i.e. the FVM holds. We conclude that martingale (or random walk) prices are not a necessary consequence of efficient stock markets. Of course, prices may well indeed follow a random walk under the FVM. But this will depend entirely on the dividend process itself being a random walk, i.e.  $\rho=1$  in (1.14). In this case, in fact,  $a=\mu(1+r)/r^2$  and  $b=1/r$  in the pricing function (1.15), and the price process in (1.16) becomes itself a random walk. Also, since dividends are usually distributed only a few times a year, the link between the dividend and the price processes will not regard monthly or weekly frequencies. It is however important to retain a distinction between FVM efficiency and random walk prices, since the generating process of dividends is entirely dependent on firms' profitability and internal financing decisions and has nothing to do with stock market efficiency *per se*.

In the sequel, we shall confine the term 'martingale restriction' to the equilibrium condition (1.2). The first part of

Chapter 3 will be dedicated to a more detailed analysis of (1.2), which will be given a clearer economic interpretation by means of a general equilibrium model of asset pricing which allows us to endogenise the expected rate of return. This will be preceded in Chapter 2 by a discussion of various testing procedures which have been employed in the past to check the empirical validity of the mainstream version of the FVM, given by equation (1.8) (with  $B_t=0$ ).

## CHAPTER 2

### TESTING FOR EFFICIENCY

#### I. The orthogonality tests.

For almost three decades now, the EMT has been the target of extensive scrutiny among financial economists. A voluminous literature and a ponderous battery of tests have been produced on the subject, with a vast majority of them suggesting that stock markets do not show significant departures from the ideal representation of the FVM.

The hypothesis often subject to test has been the simplified version of the FVM in equation (1.6). If the FVM is correct, available information should be immediately reflected in prices. It follows that the one-period rate of return  $r_t$  should be orthogonal to all current and past information and a regression of  $r_t$  on any set of variables in  $\{\Phi_t\}$  should result in an intercept coefficient equal to  $r$ , while all other coefficients should not differ from zero. As a consequence, no given trading rule based on current information

should ever enable investors to systematically beat the market and earn a rate of return higher than  $r$ . As it is well-known, traditional orthogonality tests have taken three forms: 1) weak efficiency tests, concentrating on the subset of  $\{\Phi_t\}$  containing past rates of return; 2) semi-strong efficiency tests, investigating investors' reaction to other publicly available information; 3) strong efficiency tests, focusing on the reaction to private and costly information.

It is not our purpose in this study to re-examine the history of orthogonality tests.<sup>1</sup> Rather, we want to illustrate some general points about the statistical properties of these tests and to comment on their status of generally accepted evidence in favour of stock market efficiency. The common purpose of the tests is to check whether current information can help predict future returns. Thus returns are regressed against various lagged variables of interest and the null hypothesis of zero coefficients is tested against the non-zero alternative. However, unlike most other economists, who spend much time and energy looking for significant (i.e. non-zero) coefficients in order to support their claims, efficient market theorists are used to look in quite the opposite direction, and regard zero coefficients as evidence in favour of the EMT. If current information cannot help predict future returns - so they claim - it

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1. A detailed account of various orthogonality tests can be found in Fama (1965,1970,1976), Jensen (1972), Jensen et al. (1978) and Brealey (1983). In the introduction to the 1978 symposium Jensen contended that the efficiency hypothesis is the best established empirical fact in economics.

follows that investors have already discounted it, hence it is already reflected in current prices.

This singular way to support the efficiency hypothesis can hardly sound too convincing. As James Tobin (1987) put it, efficiency theorists play a game in which they win when they lose. Zero coefficients on some lagged variables show that those variables do not help predicting current returns. However, this is a long way from proving that the variables are already discounted in current prices, since zero coefficients might be due to a host of different reasons totally unrelated to informational efficiency. Obviously, orthogonality results do suggest that available information cannot be easily employed to generate useful price forecasts and that, as a consequence, beating the market is no easy job (after all, predictions can only be based on available information). But taking this difficulty as evidence in favour of the EMT is just a remarkable *non sequitur* in the history of economic analysis, which has unfortunately been taken for granted for a long time. In Chapter 5 we try to show the essence of this logical lapse and provide arguments to support the view that price changes are not only caused by the arrival of new information about future dividends but also by other factors, which do in fact make current returns depend upon past information. Some empirical evidence in favour of this conclusion is then presented in Chapter 6, where we will show that a number of

lagged variables are significantly correlated with current stock returns.

Before presenting our results, however, we will show here that traditional orthogonality tests are virtually powerless against an interesting alternative hypothesis to the FVM and that their empirical 'success' is therefore much less compelling than it purports to be. Of course, the lack of power in rejecting the alternative hypothesis reinforces our own rejection of the null.

Suppose that actual prices are generated by the following model:<sup>2</sup>

$$\ln P_t = \ln P_t^F + \zeta_t \quad (2.1)$$

$$\zeta_t = \alpha \zeta_{t-1} + \nu_t \quad \alpha < 1 \quad (2.2)$$

where  $P_t^F$  is the FVM price in equation (1.4). The model implies that the log of the actual price  $P_t$  diverges from the log of the FVM price  $P_t^F$  by a first-order autoregressive term  $\zeta_t$ , where  $\nu_t$  is a white noise process which we assume uncorrelated with the martingale difference  $\epsilon_t$  in (1.2) at each  $t$ . The model implies that market prices do deviate from FVM prices, i.e. the market incurs into valuations errors, but these errors tend to be reabsorbed in the long run. In fact, a model of this sort captures the rationale behind the activity of research-driven portfolio managers, who try to establish

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2. The model is taken from Summers (1986).

accurate estimates of  $P_t^F$  precisely because they believe that, as fundamental values tend to reassert themselves in the long run, it is indeed possible to generate positive excess returns (i.e. beat the market). Notice in fact that from (2.1)-(2.2) and the definition of  $r_t$  we can approximate the latter by:

$$\begin{aligned} r_t &= (P_{t+1} - P_t)/P_t + D_{t+1}/P_t \approx \ln P_{t+1}^F - \ln P_t^F + D_{t+1}/P_t^F \\ &= r_t^F + \zeta_{t+1} - \zeta_t = r_t^F - (1-\alpha)\zeta_t + \nu_{t+1} \end{aligned} \quad (2.3)$$

where  $r_t^F = \ln P_{t+1}^F - \ln P_t^F + D_{t+1}/P_t^F$  is the rate of return under FVM prices. It follows that:

$$\eta_t \equiv r_t - \lambda_t = \epsilon_t - (1-\alpha)\zeta_t + \nu_{t+1} \quad (2.4)$$

where remember that  $\epsilon_t = r_t^F - \lambda_t$  is the martingale difference in (1.2) and  $\lambda_t = E_t r_t^F$  is the equilibrium rate of return under the FVM. Then:

$$E_t \eta_t = - (1-\alpha)\zeta_t = (1-\alpha)(\ln P_t^F - \ln P_t) \quad (2.5)$$

and, in the special case where  $\lambda_t = r$ :

$$E_t r_t = r + (1-\alpha)(\ln P_t^F - \ln P_t) \quad (2.6)$$

Equation (2.5) shows that, under model (2.1)-(2.2), the expected excess return  $E_t \eta_t$  is not always zero, as in the EMT, but is positive if actual prices are below fundamental values and negative if they are above. Hence, as long as fundamental research can provide precise estimates of  $P_t^F$ , it is possible to use a profitable trading rule for buying and selling shares, namely: Buy if  $P_t < P_t^F$  (i.e.  $E_t \eta_t > 0$ ), sell if  $P_t > P_t^F$  (i.e.  $E_t \eta_t < 0$ ). The expected excess return in (2.5) is in fact positively dependent on the width of the gap between fundamental and actual prices, and negatively dependent on the parameter  $\alpha$ , which is a measure of the rapidity with which actual prices revert to fundamentals. For instance,  $\alpha=0.8$  on monthly data implies that it takes approximately three months to eliminate half of the valuation error  $\zeta_t$ , but if  $\alpha=0.98$  three years will be necessary. Of course, the faster the reduction of the gap, the higher is the excess return which can be earned in any one month. In the extreme cases,  $\alpha=0$  implies that the trading rule allows one to earn the full extent of the log price gap generated by the monthly noise  $\nu_t$ , while  $\alpha=1$  implies a zero expected excess return, since in this case there is no tendency for actual prices to revert to fundamentals. Hence we conclude that, in the presence of a price gap  $\zeta_t$ , the more efficient is the market the higher is the scope for research-driven portfolio management to earn excess returns. On the other hand, the latter will be zero if  $\alpha=1$ , i.e. prices do not revert to fundamentals, or if  $\nu_t=0$  for all  $t$ , i.e. the FVM holds exactly.

In order to demonstrate the lack of power of traditional orthogonality tests, let us assume that, thanks to fundamental research, we are able to obtain a time series for  $P_t^F$  for a period of, say, 360 months. We can then run a traditional orthogonality test by regressing the rate of return  $r_t$  on a constant and  $(\ln P_t^F - \ln P_t)$ , as in (2.6). Let us also assume that the market is inefficient, (i.e.  $\zeta_t \neq 0$ ) and that  $\alpha = 0.98$ , i.e. there is only a very weak tendency for actual prices to revert to fundamentals. The true value of the estimated parameter in regression (2.6) is in this case 0.02. Assuming further that the standard deviations of monthly returns and valuation errors are (plausibly enough) 20 and 30 per cent respectively, it follows that the variance of the estimated parameter ( $\sigma_\eta^2 / T\sigma_\zeta^2$ , with  $T=360$ ) is approximately equal to 0.01. Under these assumptions, the probability of accepting the null hypothesis  $\alpha=0$  (i.e. the probability of a Type-II error) at a 5% level is as high as 1/2. Hence we conclude that the orthogonality test (2.6) has very low power against the alternative model (2.1)-(2.2).<sup>3</sup>

Quite aside from this sort of strictures, however, it is really the whole interpretation of orthogonality tests which is liable to a simple general criticism. Econometric techniques are designed to shed light on the existence of possible relationships among economic variables, as suggested by economic theory. In performing this task,

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3. Obviously, the power of the test can be increased using a larger number of observations. As shown by Shiller and Perron (1985), however, the power depends more on the time span of the data than on their frequency.

however, econometrics has, before anything else, a destructive role to play, in that the filter interposed between the theory and its empirical applications must essentially provide rules to discriminate among alternative hypotheses regarding the specific form of the relationship between the variables of interest. The end result of this selection process should be, at least ideally, 'the survival of the fittest model' - the model which, despite the bombardment of tests to which has been submitted, has been robust enough to resist the attacks and adhere to its own claim, i.e. the existence of a specific relationship among certain variables. The survival of the model can then be potentially regarded as reliable empirical evidence on the actual existence of such a relationship. On the other hand, if a model fails to survive the tests, the only legitimate conclusion to be drawn from such failure is that the model is not a satisfactory representation of the underlying reality which it tries to capture, but the failure in itself can suggest absolutely nothing regarding that reality.

In the case of orthogonality tests, therefore, the only proper conclusion to be drawn from each unsuccessful attempt to find variables which are significantly correlated with stock returns is that each model fails to provide valid empirical evidence on the return generating process; whereas interpreting such failure as positive evidence on a whatsoever aspect of the return process is a totally unwarranted and misleading exercise. It should be clear, in

fact, that the real claim of orthogonality tests is not the tautological remark that return uncorrelatedness precludes the use of profitable trading rules. The claim is rather that the lack of correlation shows that information contained in the regressors has already been efficiently discounted by the market and is therefore already reflected into current prices. It is this transition from a negative to a positive statement which cannot be sustained on the basis of a correct interpretation of the econometrics behind the tests. In other words, the EMT in itself cannot distinguish between 'fundamental' and simply irrelevant information, since the testable predictions implied by the efficiency hypothesis are exactly the same in both cases.

The arguments presented above should be sufficient to cast serious doubts on the entire EMT testing apparatus based on orthogonality tests. Remember that what is called into question is neither the ineffectiveness of trading rules based on past information nor the prompt reaction of rational investors to the arrival of new information. Rather, our aim is to show that neither phenomena can be adduced as evidence that rational investors behave in such a way that stock prices are always equal to the discounted sum of expected dividends.

In the next section, we examine a body of empirical research which has the same critical aim but uses a different approach to question the validity of the FVM.

## II. The variance bound tests.

The long, widespread and well-established consensus around the efficient market hypothesis as modelled by the FVM received a vigorous shake in the early 1980's, when a new test procedure appeared which seemed to provide very strong empirical evidence against the FVM.<sup>4</sup>

The new test is based on a straightforward implication of the FVM. Define:

$$P_t^* = \sum_{i=1}^{\infty} (1+r)^{-i} D_{t+i} \quad (2.7)$$

Compared to  $P_t^F$  in (1.8),  $P_t^*$  is the infinite discounted sum of actual (as opposed to expected) dividends accruing to the holders of a share whose ex ante market price is  $P_t^F$ . Then:

$$P_t^F = E_t P_t^* \quad (2.8)$$

$$P_t^* = E_t P_t^* + u_t = P_t^F + u_t \quad (2.9)$$

Equation (2.9) describes the statistical generating mechanism of the variable  $P_t^*$  relative to the information set  $\{\Phi_t\}$ . The term  $u_t$

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4. Shiller (1981a,b) and LeRoy and Porter (1981) were the initiators of the new trend.

in (2.9) is a zero-mean disturbance which is uncorrelated with information at time  $t$  and orthogonal to the systematic component  $P_t^F$  of the generating mechanism, since:

$$E_t u_t = E_t(P_t^* - E_t P_t^*) = 0$$

$$E_t P_t^F u_t = P_t^F E_t u_t = 0$$

Notice that, while  $u_t$  is uncorrelated with information at  $t$ , it may well be serially correlated since, given (2.7),  $u_{t-i} = P_{t-i}^* - P_{t-i}^F$  is not known at time  $t$ . The market price  $P_t^F$  in (2.8) can be interpreted as the optimal forecast of  $P_t^*$  relative to information at  $t$ , and  $u_t$  in (2.9) as the corresponding forecast error. Then, as by definition optimal forecasts are uncorrelated with forecast errors (i.e.  $\text{Cov}(P_t^F, u_t) = 0$ ), it follows from (2.9) that:

$$\text{Var}(P_t^*) = \text{Var}(P_t^F) + \text{Var } u_t \quad (2.10)$$

and therefore:

$$\text{Var}(P_t^F) \leq \text{Var}(P_t^*) \quad (2.11)$$

Inequality (2.11) identifies a lower bound for the unconditional variance of stock prices. Clearly, the variance of a rational forecast (here the market price) must be lower than the

variance of the variable being forecast. Or, in other terms, the variance of the conditional mean of a distribution must be lower than the variance of the distribution itself. Hence the lower bound (2.11) provides an alternative test of the FVM. If the latter is true, the unconditional variance of the market price  $P_t^F$  cannot be larger than the unconditional variance of the ex post price  $P_t^*$ , provided that the two variances exist, are finite and can thus be computed.

Notice in this regard that, while  $P_t^F$  is observable under the null hypothesis that the FVM is true,  $P_t^*$  is not, as (2.7) is an infinite forward sum. An approximate time series for it can however be calculated by choosing appropriate values for the last observation in the available sample and the constant expected return  $r$ , and then computing past data points using the recursive formula:

$$P_t^* = (1+r)^{-1}(P_{t+1}^* + D_{t+1}) \quad (2.12)$$

which, by forward substitution, yields:

$$P_t^* = \sum_{i=1}^{T-t} (1+r)^{-i} D_{t+i} + (1+r)^{-(T-t)} P_T^* \quad (2.13)$$

where  $T$  denotes the last available observation. Notice that the weight on  $P_t^*$  of the particular value chosen for  $P_T^*$  declines as  $t$  goes back to the initial date in the sample.

A reasonable choice for the terminal value of  $P_t^*$  is the terminal value of the market price,  $P_T^F$ . Alternatively, one can use the average price over the sample. As pointed out by Mankiw et al. (1985), however, if the sample mean of  $P_t^F$  is used as the terminal value of  $P_t^*$  then it is not true that  $P_t^F = E_t P_t^*$ , as required in (2.8). Setting instead  $P_T^* = P_T^F$  allows us to interpret  $P_t^*$  as the ex post price resulting from holding the stock until time T and then selling it at the prevailing price. In this case  $P_t^*$  contains both the stream of dividends accruing to the stock until time T and the final value of the stock. It follows that  $E_t P_t^*$  is equal to  $P_t^F$  even in the presence of a rational bubble. To see this, we rewrite (2.13) with  $P_T^* = P_T$  - where  $P_t$  is the stock price in a market with bubbles, as defined in (1.8) - and let  $P_t^{**}$  be the resulting approximated value of  $P_t^*$ . Then:

$$\begin{aligned}
 P_t^{**} &= \sum_{i=1}^{\infty} (1+r)^{-i} D_{t+i} - \sum_{i=T-t}^{\infty} (1+r)^{-i} D_{t+i} + (1+r)^{-(T-t)} P_T \\
 &= P_t^* - (1+r)^{-(T-t)} (P_T^* - P_T)
 \end{aligned} \tag{2.14}$$

Now notice that, in the presence of a rational bubble, (2.9) must be rewritten as:

$$P_t^* = P_t - B_t^* + u_t \tag{2.15}$$

Hence, substituting into (2.14):

$$\begin{aligned} P^{**}_t &= P_t - B^*_t + u_t + (1+r)^{-(T-t)}(B^*_T - u_T) \\ &= P_t - [B^*_t - (1+r)^{-(T-t)}B^*_T] + [u_t - (1+r)^{-(T-t)}u_T] \end{aligned} \quad (2.16)$$

Taking expectations in (2.16), it is easy to check that  $E_t P^{**}_t = P_t$  since, from the definition of  $B^*_t$ ,  $E_t B^*_T = (1+r)^{(T-t)}B^*_t$ .

In order to obtain an approximate series for  $P^*_t$  from (2.12) we also need a value for the discount rate  $r$ . We can choose to derive different series for  $P^*_t$  using different values of  $r$ ; alternatively, we can take unconditional expectations in the FVM:

$$E(P^F_t) = \sum_{i=1}^{\infty} (1+r)^{-i} E(E_t D_{t+i}) = E(D_t)/r = E(P^F_t) \quad (2.17)$$

and, provided that the unconditional expectation of  $D_t$  and  $P_t$  exist and are constant, we can calculate  $r$  as  $E(D_t)/E(P^F_t)$  from the sample means of  $P_t$  and  $D_t$ .

An approximate series for  $P^*_t$  thus obtained is plotted against the corresponding market price in Figure 2.1. Here  $P_t$  is the annual real stock market index of the Milan Bourse from 1913 to 1987, calculated by dividing the Bank of Italy nominal index for December by the Italian Consumer Price Index. The ex post price  $P^*_t$  has been

computed assuming  $P_T^* = P_T$  and  $r = 4.675\%$ , which is the ratio of the sample means of the Bank of Italy dividend<sup>5</sup> and price series.

A simple visual inspection of the figure does actually suggest a very large violation of inequality (2.11). In fact, Table 2.1 shows that the sample variance of  $P_t$  is 5.11 times larger than the sample variance of  $P_t^*$ . Figure 2.3a shows that this conclusion is not dependent on the choice of the constant discount rate (except for very small values of  $r$ ). The choice of  $P_T^*$  and the sample period also appear to be unimportant. Shiller (1981b) and Bulkley and Tonks (1987) present similar results for the New York and the London Stock Exchanges, and it does not seem terribly hazardous to conclude that all stock markets around the world would indeed present similar results. It remains to be seen, however, whether the variance bound (2.11) can be truly regarded as a valid test of the FVM.

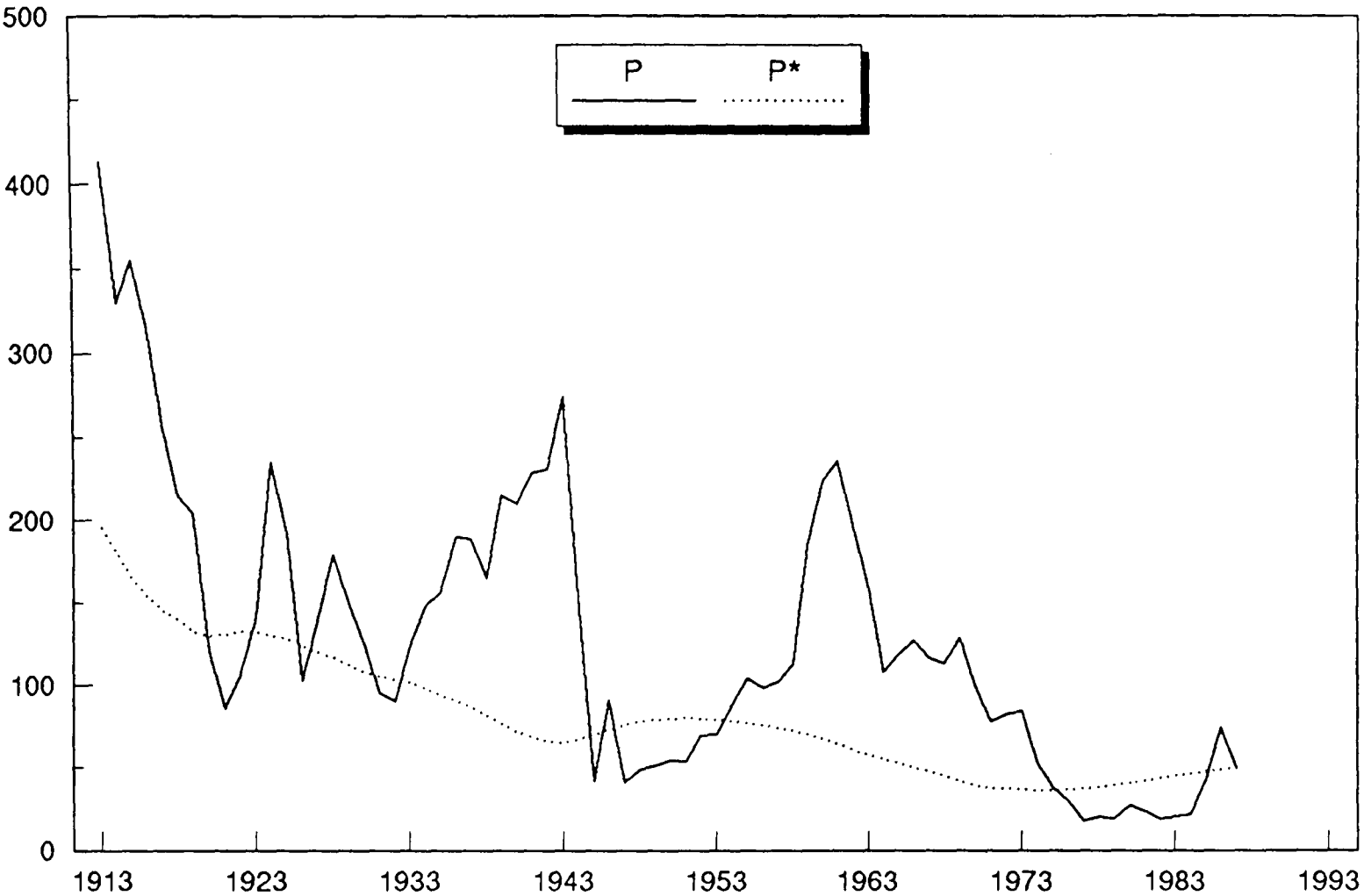
One of the first thoughts that comes to mind after observing Figure 2.1 is that the violation of the variance bound may be due to the presence of a rational bubble in the process of stock price determination. In fact, taking variances in (2.15) and noting that  $\text{Cov}(P_t, u_t) = \text{Cov}(B_t^*, u_t) = 0$  we have<sup>6</sup>:

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5. The dividend series has been obtained by multiplying the reported dividend yield series by the price series. See Appendix A.3 for a description of the data set.

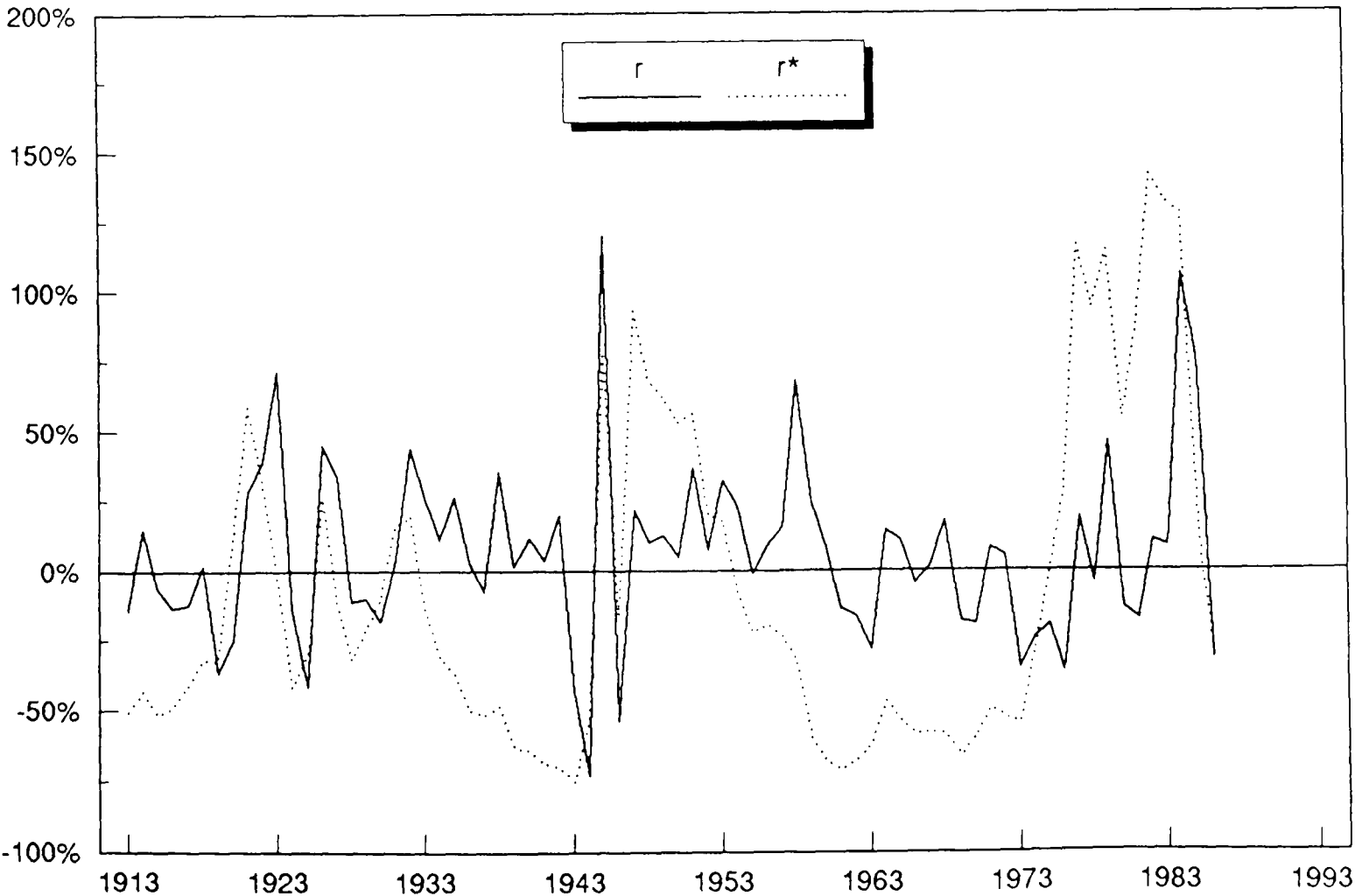
6. We assume that  $B_t^*$  is known at time  $t$ .

Figure 2.1 REAL PRICE INDEX AND EX POST PRICE



Series: Banca d'Italia Index, deflated by CPI

Figure 2.2 REAL RETURNS AND EX POST RETURNS



Series: Banca d'Italia Index, deflated by CPI

TABLE 2.1 - VARIANCE BOUND TESTS

VARIANCE RATIOS

|                                     |      |      |
|-------------------------------------|------|------|
| SHILLER (1981b), EQ. (2.11):        |      | 5.11 |
| SHILLER (1981b), EQ. (2.24):        |      | 4.79 |
| SHILLER (1981a), EQ. (2.25):        |      | 0.15 |
| LEIDON (1986b), EQ. (2.27):         | k=1  | 0.30 |
|                                     | k=2  | 0.62 |
|                                     | k=5  | 0.91 |
|                                     | k=10 | 1.67 |
| MANKIW ET AL.(1987), EQ. (2.28):    |      | 0.39 |
| LEROY AND PARKE (1987), EQ. (2.30): |      | 1.19 |
| PESARAN (1989), EQ. (2.31):         |      | 0.33 |
| WEST (1988b), EQ. (2.37):           |      | 3.10 |

DURLAUF AND HALL (1989):

|       |        |        |        |        |        |        |
|-------|--------|--------|--------|--------|--------|--------|
| i =   | 0      | 1      | 2      | 3      | 4      | 5      |
| PFi   | 61.49% | 68.45% | 74.25% | 78.01% | 81.44% | 83.14% |
| DFi   | 18.24% | 16.53% | 19.64% | 19.87% | 19.97% | 22.72% |
| PDFi  | 90.41% | 91.83% | 91.98% | 91.23% | 90.61% | 91.46% |
| DPFi  | 2.51%  | 9.02%  | 14.14% | 20.20% | 28.08% | 37.49% |
| DPDFi | 8.37%  | 24.64% | 33.40% | 42.19% | 50.69% | 55.91% |

Discount rate = 4.675%

Data source: Banca d'Italia Index for December, deflated by CPI  
Period: 1913 - 1987

Figure 2.3a

SHILLER

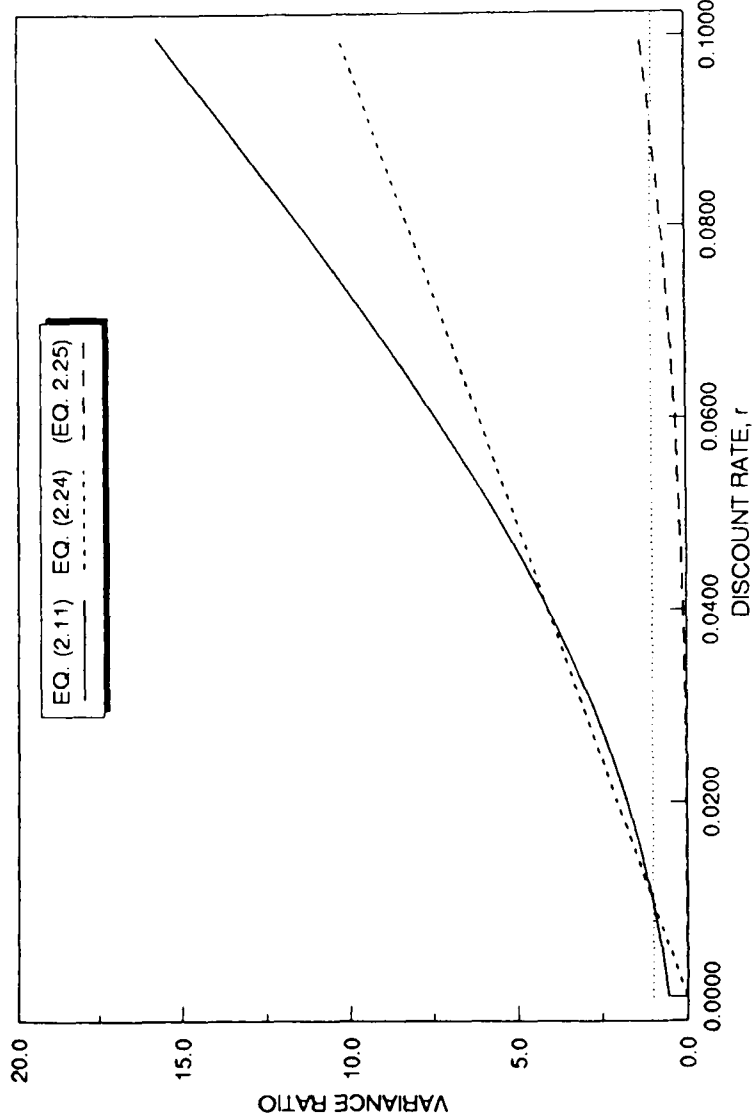


Figure 2.3b

KLEIDON

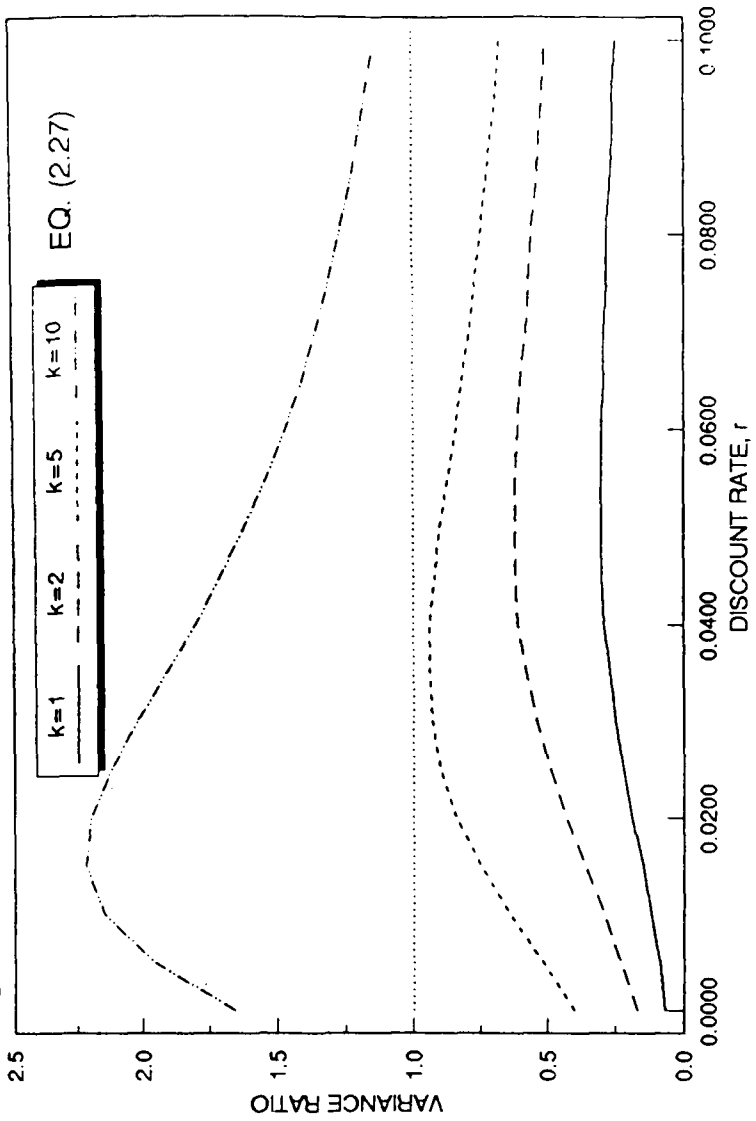


Figure 2.3c

MANKIW ET. AL

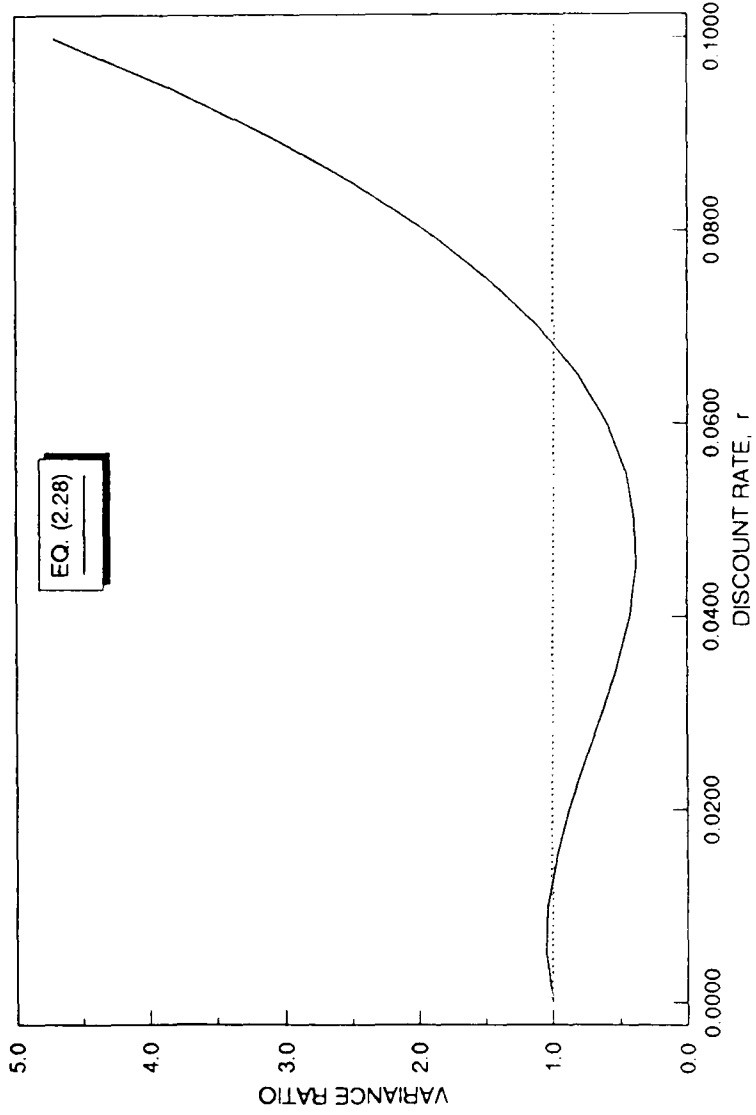


Figure 2.3d

LEROY & PARKE

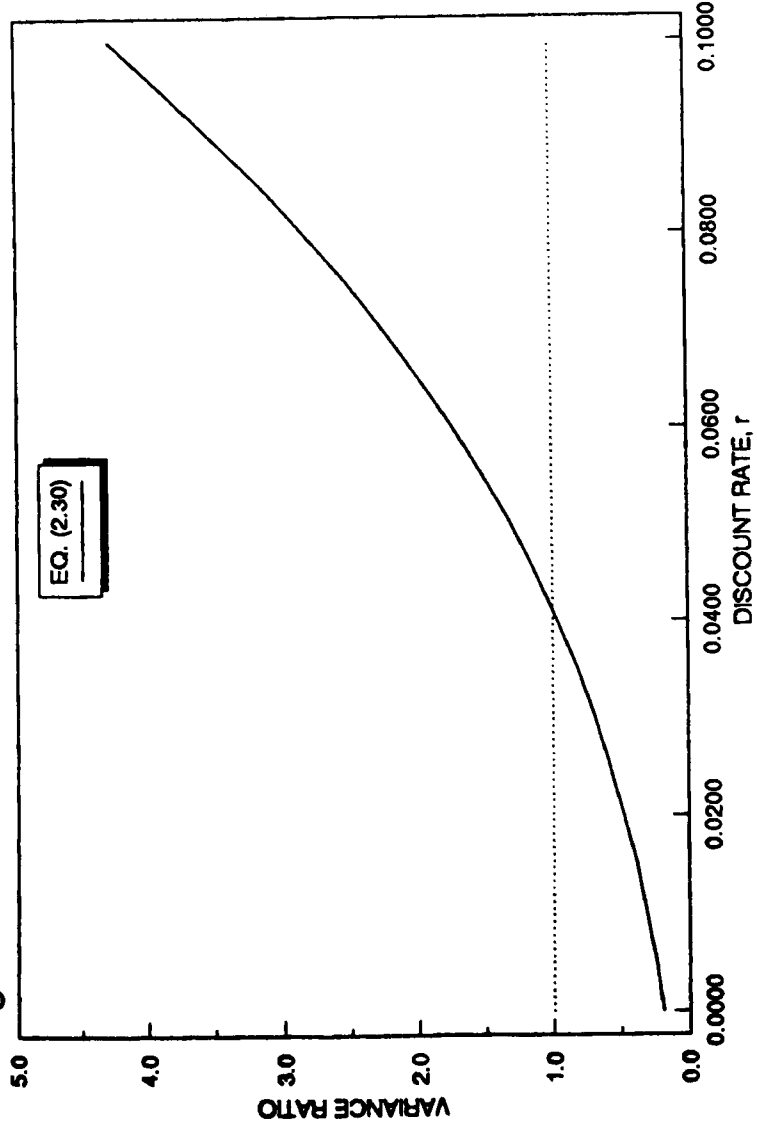


Figure 2.3e

PESARAN

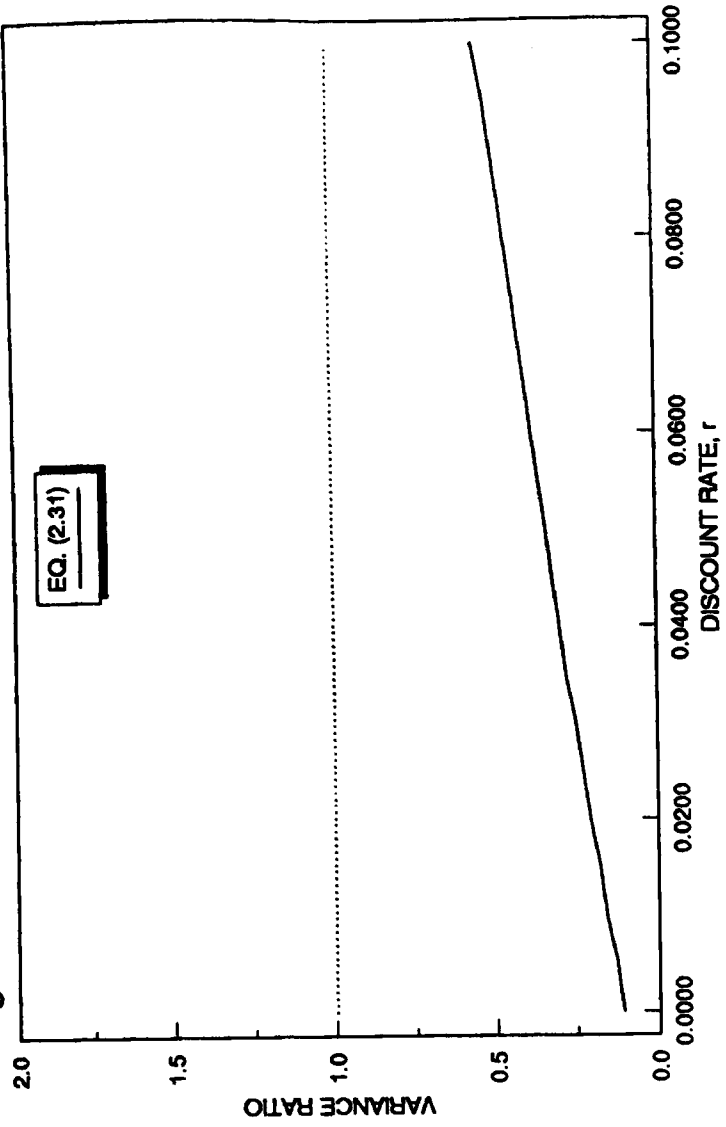
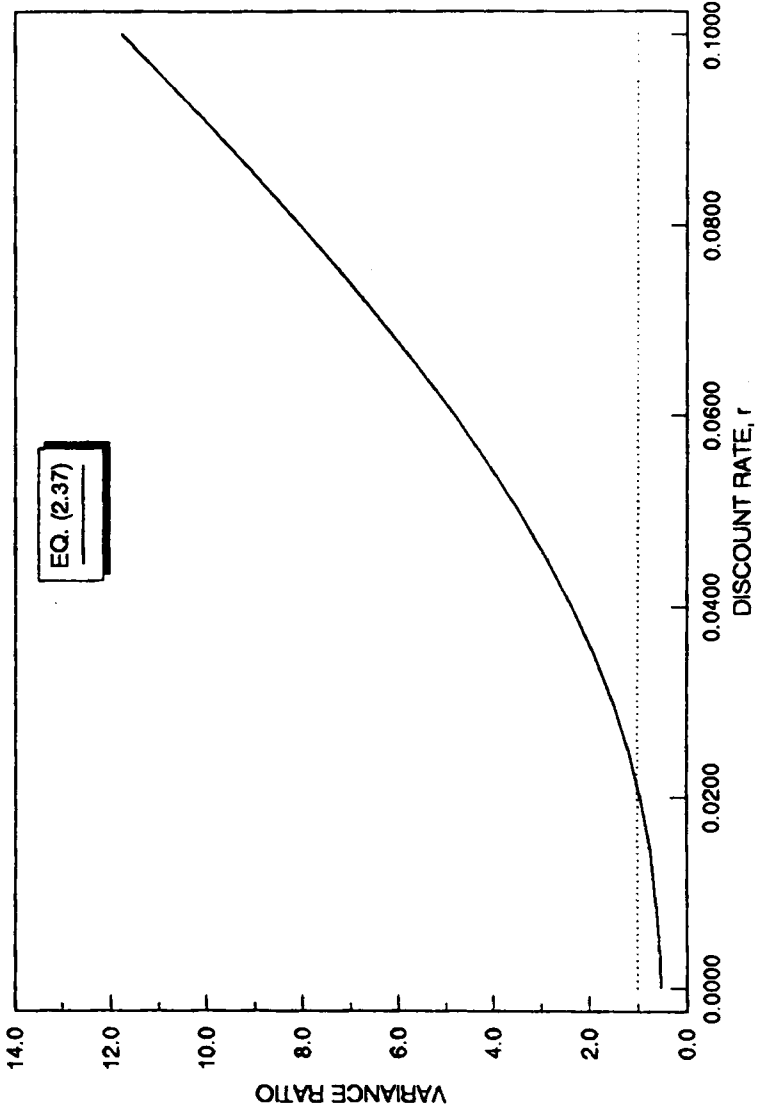


Figure 2.3f

WEST



$$\text{Var}(P_t^*) = \text{Var}(P_t) + \text{Var}(B_t^*) + \text{Var}(u_t) - 2\text{Cov}(P_t, B_t^*) \quad (2.18)$$

Hence the variance of  $P_t$  could well be greater than the variance of  $P_t^*$ , provided that the covariance between the price and the bubble is positive and sufficiently large. Although conceivable in theory, however, the possibility that bubbles may account for the observed excess volatility is ruled out in practice by the way in which the approximate  $P_t^*$  is constructed in (2.14). Taking variances in (2.16), in fact, we obtain:

$$\begin{aligned} \text{Var}(P_t^{**}) &= \text{Var}(P_t) + \text{Var}[B_t^* - (1+r)^{-(T-t)} B_T^*] \\ &+ \text{Var}[u_t - (1+r)^{-(T-t)} u_T] + 2\text{Cov}[P_t, (B_t^* - (1+r)^{-(T-t)} B_T^*)] \end{aligned} \quad (2.19)$$

But since  $E_t[B_t^* - (1+r)^{-(T-t)} B_T^*] = 0$ , then  $B_t^* - (1+r)^{-(T-t)} B_T^*$  is orthogonal to current information. Hence  $\text{Cov}[P_t, B_t^* - (1+r)^{-(T-t)} B_T^*] = 0$  in (2.19) and we conclude that the existence of a rational bubble cannot explain the empirical violation of the variance bound (2.11). The reason is clearly that the approximation of  $P_t^*$  in (2.14) effectively incorporates the bubble into the null hypothesis subject to test. Hence bubbles must be ruled out as a possible explanation for the violation of the variance bound since, under the EMT, the variance of  $P_t^{**}$  would be greater than the variance of  $P_t$  even in the

presence of a bubble.<sup>7</sup> Accordingly, in order to investigate other possible explanations, we shall refer back to the bubbleless FVM and the variance bound (2.11).

The reader will have already noticed that, in order to perform the test, an important assumption is needed on the stochastic processes generating prices and dividends. Remember that a stochastic process is a sequence of random variables ordered by  $t$ . A time series can be seen as a single realization of a stochastic process, and each observation in the series as a random drawing from the probability distribution associated with the variable. In general, this distribution will have a mean and a variance: for  $P_t$  and  $P_t^*$ , for instance, the latter appear in the inequality (2.11). It is indeed for these variances that the inequality holds. They refer to different random variables at each  $t$  and, in principle, can be neither observed nor estimated, since all we possess at each  $t$  are single observations, i.e. the time series realizations of the stochastic processes. While impossible in general, however, the efficient estimation of the variances in (2.11) becomes possible if the stochastic processes in question are (at least weakly) stationary. In this case their means and variances are constant across time, hence the total number of observations in the available sample can be used to estimate them. According to the Ergodic Theorem

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7. The proof that excess volatility cannot be justified by rational bubbles has been spelled out by Flood and Hodrick (1986).

for weakly stationary processes,<sup>8</sup> finite sample means and variances will converge asymptotically towards their population values. It follows that the estimated variances of  $P_t$  and  $P^*_t$  in Table 2.1, which are calculated on a cross-section of single realizations of the two processes at different  $t$ , will be efficient estimates of the variances in (2.11) only if the processes are weakly stationary. If, on the other hand,  $\{P_t\}$  and  $\{P^*_t\}$  are nonstationary processes, inequality (2.11) will be meaningless, since in this case the population variances of the two processes will not be defined.

The need for a stationarity assumption in the dividend process, implicit in the variance bound (2.11), has been repeatedly employed to challenge the validity of (2.11) as a test of the FVM.<sup>9</sup> In order to understand the argument, let us again assume that dividends follow a (weakly stationary) first-order autoregressive process, as in (1.14):

$$D_t = \mu + \rho D_{t-1} + \xi_t \quad (2.20)$$

In this case the population mean and variance of  $D_t$ , which are equal to  $E(D_t)=\mu/(1-\rho)$  and  $\text{Var}(D_t)=\sigma^2/(1-\rho^2)$ , are indeed finite constants and can therefore be efficiently estimated using the

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8. See, e.g., Grimmett and Stirzaker (1982, p. 243).

9. See, inter alia, Flavin (1983), Kleidon (1986a,b,c), Marsh and Merton (1986). The following example is taken from Kleidon (1986b).

available sample data. As we already know, if dividends follow the process (2.20), prices will also follow a similar process, provided that they move according to the FVM, namely:

$$P_t^F = \mu/r + \rho P_{t-1}^F + b\xi_t \quad (2.21)$$

where  $b=\rho/(1+r-\rho)$ ,  $E(P_t^F)=\mu/[r(1-\rho)]$  and  $\text{Var}(P_t^F)=b^2\sigma^2/(1-\rho^2)$  are all finite constants. Notice that, as expected,  $E(D_t)/E(P_t^F)=r$ . As for  $P_t^*$ , we have, from (2.12) and (2.20):

$$[1+(1+r)^{-1}F]P_t^* = (1+r)^{-1}D_{t+1} = [(1+\rho L)(1+r)]^{-1}(\mu+\xi_{t+1})$$

where  $F$  and  $L$  are the forward and lag operators respectively. Hence, thanks to the multiplicity of ARMA models<sup>10</sup>, we can write:

$$(1+\rho L)[1+(1+r)^{-1}L]P_t^* = (1+r)^{-1}(\mu+\xi_{t+1})$$

and rearranging:

$$P_t^* = [(1-\theta_1 L - \theta_2 L^2)(1+r)]^{-1}(\mu+\omega_{t+1}) \quad (2.22)$$

where  $\theta_1=\rho+(1+r)^{-1}$ ,  $\theta_2=-\rho(1+r)^{-1}$  and  $\omega_t$  is a white noise process similar to  $\xi_t$ . Thus, under the FVM and assuming AR1 dividends,  $P_t^*$

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10. See Box and Jenkins (1976).

will have an AR2 form, with  $E(P_t^*) = \mu/r(1-\rho) = E(P_t)$  and  $\text{Var}(P_t^*) = [(1+r+\rho)/(1+r-\rho)]\{\sigma^2/[(r^2+2r)(1-\rho^2)]\}$ . Notice also that  $\theta_1 + \theta_2 = (1+\rho r)/(1+r)$ , so that  $\rho=1$  implies  $\theta_1 + \theta_2 = 1$ . Hence a unit root in the dividend process implies a unit root in both the  $P_t$  and the  $P_t^*$  process. In addition:

$$\text{Var}(P_t^F)/\text{Var}(P_t^*) = [\rho^2(r^2+2r)]/[(1+r)^2-\rho^2] < 1 \quad (2.23)$$

for  $\rho \neq 1$ . Hence, provided that dividends (and consequently  $P_t^F$  and  $P_t^*$ ) follow stationary processes, inequality (2.11) is duly verified under the FVM. Notice, on the other hand, that (2.23) equals one if  $\rho=1$ . Therefore, if dividends (hence  $P_t^F$  and  $P_t^*$ ) have a unit root, the variances in (2.11) will be undefined, while their limit as  $\rho$  tends to 1 will be infinite and their ratio will equal unity. Indeed, Monte Carlo analysis<sup>11</sup> shows that the presence of non stationarity makes variance bound tests like (2.11) severely biased towards rejection of the FVM.

We can estimate the importance of the stationarity assumption for Shiller's variance bound tests by looking at two additional variance ratios from Shiller (1981b, eq. 13) and Shiller (1981a, eq. I.3), which are reported for our Italian sample in Table 2.1. The ratios originate from the following inequalities:

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11. See Kleidon (1986a) and West (1988b).

$$\text{Var}(\Delta P_t) \leq \text{Var}(D_t)/(2r) \quad (2.24)$$

$$\text{Var}(\Delta P_t) \leq \text{Var}(\Delta D_t)/[2r^3/(1+2r)] \quad (2.25)$$

which, like (2.11), hold under the FVM, combined with additional assumptions on the distribution of dividends and prices. In particular, (2.24) requires weak stationarity of  $P_t$  and  $D_t$  (like (2.11)), whereas (2.25) is derived under the assumption that dividends and prices are non stationary in levels but stationary in first differences. Table 2.1 and Figure 2.3a show that the variance bound (2.24) is again violated in our Italian sample for all relevant values of the discount rate. However, the same is not true for the variance bound (2.25). As in Shiller, our data show that the price variance bound derived under the assumption of non stationary dividends and prices fails to reject the EMT.<sup>12</sup>

Because of such discrepancy of results, the issue of non stationarity has given rise to a rich literature on variance bound tests, which has concentrated on the attempt to develop tests that would be robust to non stationary data. Building on Shiller's controversial evidence, Kleidon (1986b) constructs a new variance bound test under the assumption that prices follow a geometric random walk:<sup>13</sup>

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12. Figure 2.3a shows that the variance ratio from (2.25) is greater than one only for very large values of  $r$ .

13. The simple arithmetic random walk model in (2.21) with  $\rho=1$  has the undesirable property that the expected capital gain varies inversely with the price level.

$$\ln P_t = \mu + \ln P_{t-1} + \xi_t \quad (2.26)$$

From (2.26),  $P_t = P_{t-1} \exp(\mu + \xi_t)$  and, assuming log-normality of  $\exp(\mu + \xi_t)$ , the expected capital gain is a constant  $g$  equal to  $\exp(\mu + \sigma^2/2) - 1$ , where  $\sigma^2$  is the variance of  $\xi_t$ . In addition, notice that a variance bound like (2.11) applies also to conditional variances (which, unlike unconditional variances, are defined for random walks). Hence we can write:

$$\text{Var}(P_{t+k} | P_t) = P_t^2 \text{Var}[\exp(k\mu + \sum_{i=1}^k \xi_{t+i})]$$

and therefore:

$$\text{Var}(P_{t+k}/P_t | P_t) \leq \text{Var}(P_{t+k}^*/P_t | P_t) \quad (2.27)$$

where  $\text{Var}(P_{t+k}/P_t | P_t) = E\{[P_{t+k} - E(P_{t+k} | P_t)]/P_t\}^2$ ,  $\text{Var}(P_{t+k}^*/P_t | P_t) = E\{[P_{t+k}^* - E(P_{t+k}^* | P_t)]/P_t\}^2$  and  $E(P_{t+k} | P_t) = E(P_{t+k}^* | P_t) = P_t(1+g)^k$ .

The ratio between the two variances in (2.27), for  $k=1,2,5,10$  is reported for Italian data in Table 2.1. As for (2.25), results suggest that, once non stationarity of dividends and prices is properly accounted for, the variance bound test (2.27) is unable to reject the EMT. Figure 2.3b shows that, unlike Shiller's, Kleidon's

ratios have a peak in the region of  $r=4.50\%$  and start declining thereafter. Also, the value of the ratio increases with the horizon  $k$ , and is actually larger than one for  $k=10$ . Again, results on our Italian sample are substantially similar to Kleidon's results on US data (see Kleidon (1986b), Table 3, p.986).

The idea that correcting for non stationarity would unequivocally reverse the conclusions drawn from Shiller's original variance bound test has been challenged by Mankiw, Romer and Shapiro (1985). They derive a variance bound by comparing the rational price forecast  $P_t^F$  to a 'naive' price forecast  $P_t^N$ , based on static dividend expectations. In such a case,  $P_t^N = D_t/r$  and from (2.9):

$$E(P_t^F - D_t/r)^2 \leq E(P_t^* - D_t/r)^2 \quad (2.28)$$

Notice that subtracting  $D_t/r$  from  $P_t^F$  and  $P_t^*$  is equivalent to removing a stochastic linear trend from the series. In fact, by rearranging the FVM equation (1.7), we can write:

$$P_t^F - D_t/r = [(1+r)/r] \sum_{i=1}^{\infty} (1+r)^{-i} E_t \Delta D_{t+i} \quad (2.29)$$

Hence, provided that dividends are stationary in first differences, the linear combinations  $P_t^F - D_t/r$  (and hence  $P_t^* - D_t/r$ ) are stationary under the constant expected return FVM, i.e. prices

and dividends are cointegrated, with the cointegrating parameter equal to the inverse of the discount rate  $r$ .<sup>14</sup> It follows that the two sides of inequality (2.28) are defined under an arithmetic random walk model for dividends and prices. Mankiw et al. provide evidence based on (2.28) which rejects the FVM on US data for all relevant values of the constant discount rate. However, as shown in Table 2.1 and in Figure 2.3c, results are not so clear-cut on our Italian sample. In fact, the ratio between the two quantities in (2.28) is lower than one for a particularly plausible range of discount rates.

On the other hand, LeRoy and Parke (1987) develop a multiplicative version of (2.28) under the assumption of a geometric random walk model for prices and dividends (as in Kleidon). Their variance bound takes the form:

$$\text{Var}(P_t/D_t) \leq \text{Var}(P_t^*/D_t) \quad (2.30)$$

In this case the evidence on US data is in favour of the FVM. But notice from Table 2.1 and Figure 2.3d that inequality (2.30) is violated on our Italian data for values of the discount rate above 4.00%. Hence we conclude that allowing for non stationarity of the data does not necessarily provide unambiguous evidence in favour or against the FVM, on US as well as on Italian data.

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14. See Engle and Granger (1987). Notice that, as we already know from Chapter 1, if dividends follow a random walk with drift  $\mu$ , the linear combination (2.29) equals the constant  $a = \mu(1+r)/r^2$  under the simplified FVM.

All the above tests are derived under different auxiliary assumptions regarding the distribution of dividends and prices. However, Pesaran (1989) has recently proposed a simple way to sidestep the non stationarity issue, without relying on auxiliary distributional assumptions. To understand his method, notice that, from the definition of  $P_t$ , we can write:

$$P_t = (1+r)^{-1}(P_{t+1}+D_{t+1}) - (1+r)^{-1}v_t \quad (2.31)$$

where  $v_t = (P_{t+1}+D_{t+1}) - E_t(P_{t+1}+D_{t+1})$  is a martingale difference process equal to  $\epsilon_t P_t$ , and  $\epsilon_t$  is defined under (1.2). Subtracting (2.31) from (2.12) we can write:

$$P_t^* - P_t = (1+r)^{-1}(P_{t+1}^* - P_{t+1}) + (1+r)^{-1}v_t$$

and, by forward substitution:

$$P_t^* - P_t = (1+r)^{T-t}(P_T^* - P_T) + \sum_{i=1}^{T-t} (1+r)^{-i} v_{t+i-1}$$

Hence, using the approximation  $P_T^* = P_T$ , we obtain:<sup>15</sup>

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15. Notice again that, with  $P_T^* = P_T$ , (2.24) holds even in the presence of a rational bubble. Hence all variance bound tests derived from (2.24) will be unable to detect the presence of such bubbles.

$$P_t^* = P_t + \sum_{i=1}^{T-t} (1+r)^{-i} v_{t+i} - 1 \quad (2.32)$$

and therefore:

$$r_t^* = r_t + \sum_{i=1}^{T-t} (1+r)^{-i} (v_{t+i}/P_t) \quad (2.33)$$

where  $r_t^* = (P_{t+1}^* + D_{t+1})/P_t$  is the one-period ex post real rate of return. From (2.33), a new variance bound can be obtained, involving rates of return instead of prices. In fact:

$$\text{Var}(r_t^*) = \text{Var}(r_t) + \sum_{i=1}^{T-t} (1+r)^{-2i} \text{Var}(v_{t+i}/P_t) \quad (2.34)$$

and therefore:

$$\text{Var}(r_t) \leq \text{Var}(r_t^*) \quad (2.35)$$

The distinctive feature of Pesaran's variance bound is that it is immune from the problems created by non stationarity, while at the same time it does not require auxiliary assumptions on the distribution of dividends and prices. Contrary to prices, in fact, rates of return can safely be assumed to follow a stationary process,

as we shall indeed demonstrate for our Italian data in Chapter 4 by running a Dickey-Fuller test on  $r_t$ .<sup>16</sup> Table 2.1 and Figure 2.2 show that, when calculated on our data, the ratio of the sample variances of  $r_t$  and  $r_t^*$  is well below unity, as implied by the FVM. Figure 2.3e shows that the result is not sensitive to the choice of  $r$ . Pesaran (1989) presents similar results obtained on Shiller's data.

Finally, a test similar to (2.28) and (2.30) has been constructed by West (1988a) from an original idea by Blanchard and Watson (1982). The test compares innovation variances rather than level variances, and takes the form:

$$\text{Var}(P_t^F - P_t^*) \leq \text{Var}(P_t^\Psi - P_t^*) \quad (2.36)$$

where  $\{\Psi_t\}$  is a subset of the information set  $\{\Phi_t\}$  containing at least current and lagged dividends, and  $P_t^\Psi = E(P_t^* | \Psi_t)$ . In the simpler case in which  $P_t^*$  is uncorrelated with  $\{\Psi_t\}$ ,  $P_t^\Psi = 0$  and (2.36) can be written as:

$$\text{Var}(P_t^F - P_t^*) \leq \text{Var}(P_t^*) \quad (2.37)$$

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16. In addition, as pointed out by Pesaran (1989), the finiteness of the variance of  $r_t$  can be advocated on the grounds that one-period rates of return are bounded from below at -1, since an investor cannot lose more than what is invested, and bounded from above because real (as opposed to nominal) returns cannot be infinite within a finite period.

The ratio of the two variances in (2.37) is reported for our Italian sample in Table 2.1 and in Figure 2.3f for different values of  $r$ . Results are similar to those obtained on LeRoy and Parke's test and suggest a rejection of the FVM. West (1988a) obtains similar results on US data, under the assumption that  $P_t^*$  is correlated with current and past dividends.

The set of results presented above are a good example of the controversial nature of the variance bound evidence. The debate over the stationarity issue, which has characterized the variance bound literature in the 1980's, is still a focal point of debate in the area, where a fully satisfactory solution has yet to be found.<sup>17</sup> It has recently become clear, however, that variance bound tests are less powerful in detecting departures from the FVM, compared to suitable versions of orthogonality tests. In fact, the latter can be shown to imply, but not be implied by, their corresponding variance bound tests. This point has been forcibly argued in a recent paper by Durlauf and Hall (1989).

Building on Scott (1985), Durlauf and Hall adopt a model which, like Summer (1986) examined in the previous section, allows actual prices to diverge from fundamental values. The model is a level version of equation (2.1):

$$P_t = P_t^F + Z_t \quad (2.38)$$

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17. West (1988b) and LeRoy (1989) contain useful reviews of the literature.

which, combined with (2.9), implies:

$$P_t - P_t^* = Z_t - u_t \quad (2.39)$$

Since  $u_t$  is orthogonal to information at time  $t$ , equation (2.39) implies that the projection of  $P_t - P_t^*$  onto variables observable at  $t$  is equal to the projection of the model noise  $Z_t$  on such variables. Call  $Z_t|_t$  such projection. Then:

$$Z_t = Z_t|_t + \zeta_t$$

and therefore:

$$\text{Var}(Z_t|_t) \leq \text{Var}(Z_t) \quad (2.40)$$

since by definition  $\zeta_t$  is orthogonal to the projection.

All tests of the FVM are based on the null hypothesis  $Z_t=0$ , i.e.  $P_t - P_t^*$  is an expectation error orthogonal to information available at  $t$ . Obviously, the larger the information set, the more powerful the test, i.e. the lower the variance bound for  $Z_t$  in (2.40). For instance, the orthogonality test corresponding to Shiller's variance bound test has the form:

$$P_t - P_t^* = \beta P_t + u_t \quad (2.41)$$

where the null is  $\beta=0$ . Notice however that this is not the null hypothesis implied by Shiller's variance bound (2.11). In fact, since  $\text{Var}(P_t - P_t^*) = \text{Var}(P_t) + \text{Var}(P_t^*) - 2\text{Cov}(P_t, P_t^*)$ , inequality (2.11) implies  $\text{Var}(P_t - P_t^*) - 2\text{Var}(P_t) \geq -2\text{Cov}(P_t, P_t^*)$  and therefore:

$$\text{Var}(P_t - P_t^*) / 2\text{Var}(P_t) \geq 1 - \text{Cov}(P_t, P_t^*) / \text{Var}(P_t) \quad (2.42)$$

Notice that the right hand side of (2.42) is equal to the estimated coefficient in (2.41),  $\beta = \text{Cov}(P_t - P_t^*, P_t) / \text{Var}(P_t)$ . Hence the null implicit in (2.11) is  $\beta \leq \text{Var}(P_t - P_t^*) / 2\text{Var}(P_t)$ , and we conclude that Shiller's variance bound test is weaker than the corresponding orthogonality test is detecting departures from the FVM.<sup>18</sup> Similarly, Pesaran's variance bound (2.31) implies that the coefficient of a regression of the return discrepancy  $r_t - r_t^*$  on  $r_t$  is smaller than or equal to  $\text{Var}(r_t - r_t^*) / 2\text{Var}(r_t)$  while, from (2.33), the corresponding orthogonality null is that the coefficient equals zero.

West's variance bound test (2.36) is also weaker than its corresponding orthogonality test. In fact, we can always write  $\text{Var}(P_t^\Psi - P_t^*) = \text{Var}(P_t - P_t^*) + \text{Var}(P_t - P_t^\Psi) - 2\text{Cov}(P_t - P_t^*, P_t - P_t^\Psi)$ . Hence

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18. This point, which runs counter to Shiller's original beliefs, is also made in Pesaran (1989). Notice that, by the same procedure, a more convenient way to test Shiller's null in regression form is to test for  $\gamma \leq 1/2$  in the regression  $P_t = \gamma(P_t - P_t^*) + v_t$ .

(2.36) implies  $2\text{Cov}(P_t - P_t^*, P_t - P_t^\Psi) \leq \text{Var}(P_t - P_t^\Psi)$  and hence  $\delta \leq 1/2$  in the regression:

$$P_t - P_t^* = \delta(P_t - P_t^\Psi) + w_t \quad (2.43)$$

while the null of the corresponding orthogonality test is simply  $\delta=0$ , as in (2.41).<sup>19</sup>

The orthogonality test developed by Durlauf and Hall involves projecting the price discrepancy  $P_t - P_t^*$  onto current and past prices and dividends, using OLS. The variance of such projection is then compared to the variance of  $P_t - P_t^*$ , and the ratio between the two is interpreted as the fraction of  $\text{Var}(P_t - P_t^*)$  explained by noise. Since the projection of  $P_t - P_t^*$  is a conservative estimate of the noise  $Z_t$ , and  $Z_t=0$  under the FVM, we would expect  $\text{Var}(Z_t|t)/\text{Var}(P_t - P_t^*)$  to be zero if the FVM is true.

On the bottom of Table 2.1 we report values of the Durlauf-Hall variance ratios on our Italian sample under different information sets: PFi is the value of the ratio when the price discrepancy  $P_t - P_t^*$  is projected on current and lagged prices (from lag 0 to lag  $i$ , with  $i=0, \dots, 5$ ), DF $i$  is the ratio when the projection is on current and lagged dividends, and PDF $i$  is the ratio obtained when regressors include current and lagged prices as well as dividends. Durlauf and Hall compute these variance ratios on Shiller's data set and strongly

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19. Actually, (2.43) reduces to (2.41) in the simpler case in which  $P_t^\Psi=0$ .

reject the hypothesis that the noise variance is equal to zero. In fact, all variance ratios are considerably greater than zero, and are actually much closer to one, indicating that most of the variation in  $P_t - P_t^*$  can be accounted for by noise. Once again, our results parallel those obtained on US data. In particular, a comparison between the PFi and the DFi ratios reveals that current and lagged prices have a much larger explanatory power, relative to current and past dividends, in capturing noise. In fact, PF0 shows that the current price alone does most of the job, in accordance with Scott's (1985) original findings. The similarity between the PFi ratios and the PDFi ratios suggest that dividends contain little additional information on noise, relative to that already included in prices.

Notice that the above results are unlikely to be affected by unit roots in prices and dividends. In fact we know that, under the FVM null hypothesis, the price discrepancy  $P_t - P_t^*$  is stationary and the regressors are cointegrated. However, in order to check whether the implied non standard asymptotic distributions of the estimated coefficients might lead to spurious inference, Durlauf and Hall run their regression tests against first differences of prices and dividends, instead of levels. Their results confirm the presence of noise, as do our results. On Table 2.1, DPFi and DPDFi are the values of the variance ratios when the price discrepancy is regressed against first differences in prices and in prices and dividends respectively. Notice that, as in Durlauf and Hall, the value of the

variance ratios decreases substantially when differenced regressors are used. Since differences attenuate lower frequencies, Durlauf and Hall interpret such evidence as showing that noise is a slow moving component of stock prices - a result consistent with the long run mean reversion of prices documented in Fama and French (1988b) and Poterba and Summers (1988).

The orthogonality tests developed by Durlauf and Hall are different in character from the traditional orthogonality tests we examined in the previous section, in that they employ contemporaneous information to detect excess volatility and the presence of noise, rather than lagged information to uncover return predictability. Although the evidence provided by Durlauf and Hall against the FVM is possibly even more dramatic than Shiller's original variance bound evidence, the debate around the theoretical and statistical properties of the empirical tests of the EMT is likely to be prolonged for some time in the future. The reason is that tests of the EMT involve auxiliary assumptions which are not necessary constituents of the efficiency hypothesis, such as constant discount rates and the distribution of prices and dividends. It is our impression that the only way out of such impasse is in developing theoretically appealing alternatives to the EMT, whose empirical implications could be directly tested against the implications of the EMT. This will be the topic of Chapter 5, while in chapter 6 we show that traditional orthogonality tests can in fact be fruitfully

employed to uncover departures from efficiency, and thus provide robust evidence against the EMT.

But we still have some way to go before examining these tests. Remember that, in summarising the basic hypotheses in the FVM in Chapter 1, we noticed a crucial difference between the assumptions of constant expected rates of return and the absence of rational bubbles, on the one hand, and the assumptions of homogeneous information and rational expectations on the other. We observed that the first couple of assumptions can be relaxed without abandoning the basic tenets of the efficiency hypothesis, whereas the second couple is clearly an indispensable component of the EMT. Although the appearance of new empirical evidence based on variance bound tests has had the effect of steering the interest of economists towards a full re-examination of the EMT, subsequent research has been almost exclusively concentrated on the first couple of hypotheses. In fact, many thought that suitable versions of the Consumption Capital Asset Pricing Model, incorporating variable risk premia and expected returns, or models allowing for the presence of rational bubbles, could be the most likely candidates to supersede the FVM. The common idea is that these models would be able to reconcile the new excess volatility evidence with the essential principles of the EMT, while at the same time keeping faith to its fundamental rationality requirements. We shall analyse these models in the following chapter, while Chapter 4 will discuss the available empirical evidence

thereupon. Chapter 5 will then abandon this line of research, following our belief that the real weakness of the EMT resides in the interplay between the assumptions of homogeneous information and rational expectations.

## CHAPTER 3

### THE EXTENDED FVM

#### I. Introduction

We have seen in the previous chapter that the large amount of empirical work which has been accumulated in the past 25 years on the FVM has failed to provide convincing evidence on the most relevant issues surrounding the efficiency hypothesis. We noticed that traditional orthogonality tests are virtually powerless against interesting alternatives to the FVM and that, in any case, they can only show that current returns are uncorrelated with some, but by no means all, past information. We also saw that variance bound tests - properly adjusted to account for nonstationary data - can only provide the same sort of unsatisfactory response. Finally, we observed that, when orthogonality tests are performed using contemporaneous information, they reveal the presence of a substantial amount of noise, which is very difficult to reconcile with the EMT. In closing the chapter, we noticed that recent efforts

to enhance our understanding of stock market behaviour have been mainly focused on two possible extensions of the FVM, both of which keep the analysis within the fundamental rationality paradigm which constitutes the peculiar feature of the EMT. We investigate these two extensions in the present chapter.

## II. Asset prices in general equilibrium under risk aversion.

In Chapter 1 we observed that it is common practice in EMT literature to assume the constancy of the equilibrium rate of return, but we stopped short of analysing the economic rationale for such a hypothesis. It is now time to focus on this issue, and we shall do so in the context of a general equilibrium model of asset pricing.<sup>1</sup>

We assume an exchange economy in which a representative agent allocates his wealth between two assets: 1) a risky asset (equity), with a real rate of return  $r_t$ ; 2) a riskless asset (e.g. a short-term indexed bond), with a constant known real rate of return  $r^*$ .

The representative agent maximises the expected utility of next period's wealth:

$$\begin{aligned} \text{Max}_{\theta_t} \quad & u[E_t(A_{t+1}), -1/2 \text{Var}_t(A_{t+1})] \\ & \theta_t \end{aligned} \tag{3.1}$$

subject to  $A_{t+1} = A_t[\theta_t(1+r_t) + (1-\theta_t)(1+r^*)]$ .

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1. The model is adapted from LeRoy (1973).

In (3.1)  $u$  is a concave, strictly increasing and twice continuously differentiable utility function,  $A_t$  is wealth (stock of real assets) at time  $t$ ,  $\theta_t$  is the fraction of  $A_t$  invested in the risky asset and  $\text{Var}_t$  is the conditional variance operator. Rewriting  $A_{t+1}$  as  $\theta_t A_t (r_t - r^*) + A_t (1 + r^*)$ , we have:

$$E_t A_{t+1} = \theta_t A_t (\lambda_t - r^*) + A_t (1 + r^*) \quad (3.2)$$

$$\text{Var}_t(A_{t+1}) = (\theta_t A_t)^2 \text{Var}_t(r_t)$$

where remember that  $\lambda_t = E_t r_t$ . Hence the first-order condition of the problem is:

$$u_1(\lambda_t - r^*) - u_2 \theta_t A_t \text{Var}_t(r_t) = 0$$

where  $u_1 = u'(A_t)$  and  $u_2 = -u''(A_t)$  are the first-order derivatives of  $u$  with respect to  $E_t(\cdot)$  and  $-\text{Var}_t(\cdot)$ . Solving for  $\theta_t$ :

$$\theta_t = (\lambda_t - r^*) / [(u_2/u_1) A_t \text{Var}_t(r_t)] \quad (3.3)$$

which shows that  $\theta_t$  is positively related to the expected difference in the two assets' returns (the risk premium  $\pi_t \equiv \lambda_t - r^*$ ) and inversely related to the conditional variance of the risky return. Moreover,  $\theta_t$

is inversely related to the degree of both absolute  $(u_2/u_1)$  and relative  $((u_2/u_1)A_t)$  risk aversion.

Notice that, as the market portfolio is equivalent to a single share with value  $P_t$ , it must be the case that, in equilibrium,  $\Theta_t = P_t/A_t$ . In other words, with one market portfolio,  $\Theta_t A_t / P_t$  - the demand for units of the risky asset - must equal one. It follows that the risk premium  $\pi_t$  is equal to:

$$\pi_t \equiv \lambda_t - r^* = (u_2/u_1)P_t \text{Var}_t(r_t) \quad (3.4)$$

and the demand for units of the risky asset is:

$$\begin{aligned} \Theta_t A_t / P_t &= (\lambda_t - r^*) / [(u_2/u_1)P_t \text{Var}_t(r_t)] \\ &= [E_t(P_{t+1} + D_{t+1}) - (1+r^*)P_t] / \pi_t P_t = 1 \end{aligned} \quad (3.5)$$

We can consider three hypotheses regarding the ratio  $u_2/u_1$ :

i) **Risk neutrality.** Under risk neutrality,  $u_2/u_1=0$ , hence  $\pi_t=0$  and (3.4) reduces to (1.6), with  $r=r^*$ , the riskless rate of return.

ii) **Constant Absolute Risk Aversion (CARA).** In this case,  $u_2/u_1 = -u''/u' = k^A$ , where  $k^A$  is the coefficient of constant absolute risk aversion, according to the Arrow-Pratt measure. Hence (3.4) becomes:

$$\pi_t = k^A P_t \text{Var}_t(r_t) = k^A \Theta_t A_t \text{Var}_t(r_t) \quad (3.6)$$

which shows that the risk premium is positively related to the coefficient of absolute risk aversion, the proportion of wealth invested in the risky asset, the level of wealth itself (a direct consequence of CARA), and the variance of the risky return, which represents the traditional measure of asset riskiness.

iii) **Constant Relative Risk Aversion (CRRA)**. If  $(u_2/u_1)A_t = k^R$ , where  $k^R$  is the Arrow-Pratt measure of constant relative risk aversion, (3.4) becomes:

$$\pi_t = k^R (P_t/A_t) \text{Var}_t(r_t) = k^R \Theta_t \text{Var}_t(r_t) \quad (3.7)$$

Hence under CRRA the risk premium is a direct function of the coefficient of relative risk aversion, the proportion of wealth invested in the risky asset and the degree of asset riskiness.<sup>2</sup>

Notice then an important consequence of the new set-up. Unlike (1.6) in the FVM, the market equilibrium condition (3.4) is no longer expressed only in terms of conditional expected returns: the conditional variance of the risky return also plays a role in the determination of equilibrium, along with the shape of the utility

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2. Notice that, with  $\Theta_t = \Theta$ , i.e. a constant proportion of wealth is invested in the two assets, (3.7) becomes  $\pi_t = \gamma \text{Var}(r_t)$ , as in Merton (1980). A constant  $\Theta_t$  is a time-invariant policy function - a typical result of discounted dynamic programming. See, e.g., Sargent (1987), Chapter 1.

function, as represented by the ratio  $u_2/u_1$ . In fact, equation (3.4) is a generalisation of the martingale restriction (1.6), and reduces to (1.6) for  $\pi_t = \text{constant}$ . In this case (1.6) holds, with  $r$  re-interpreted as a risk-adjusted constant discount rate. Notice, from (3.4), that risk neutrality (i.e. a linear utility function) is a sufficient condition for (1.6) to hold. Indeed, this makes good economic sense, since (1.6) is based on the assumption that market equilibrium can be expressed in terms of expected returns only, and by definition risk-neutral investors care only about the first moment of the return distribution. But if  $\pi_t$  is not constant, (1.6) does not hold.<sup>3</sup>

The importance of this remark lies in the fact that, as we know from the previous chapter, the concept of efficiency has been commonly associated in the finance literature with the martingale restriction (1.6), although there is in fact no necessary link between (1.6) and efficiency. In the model presented above, prices still reflect only fundamental information. However, information affects not only expected dividends but also the perceived variance of returns. It follows that traditional orthogonality tests, based on the martingale restriction (1.6), are in fact joint tests of the EMT and the constant risk premium assumption. Therefore, if the risk premium is not constant, a rejection of (1.6) does not necessarily

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3. LeRoy (1973) and Ohlson (1977) explore the conditions under which the risk premium may be constant under risk aversion, i.e.  $\pi > 0$ .

imply a rejection of the EMT, provided that  $\pi_t$  is correlated with past information. In such a case we can say that the expected equity return  $\lambda_t$  is predictable. But such predictability is still consistent with efficiency, since it implies that above average returns could only be achieved at the expense of a higher level of risk. Hence predictability would increase investors' expected returns, but not their expected utility.

This remark will have an important consequence in Chapter 6, where we present some empirical evidence against the EMT, based on traditional orthogonality tests. It is clear from the above analysis that, if past information is found to be significantly correlated with current returns, it may well be the case that it is merely proxying for risk. In this case our evidence could not be interpreted as a rejection of the EMT. The model presented in the following section can help us deal with this problem.

### III. The Consumption Capital Asset Pricing Model.

As typical of traditional analyses of portfolio selection, the model examined in the previous section abstracted from the consideration of consumption activity. As we shall presently see, introducing consumption into the model leads to more general and satisfactory results. In particular, under the new set-up we are able

to determine an endogenous measure of asset riskiness that relates the risk premium to the perceived pattern of consumption.

We assume an exchange economy in which a representative consumer with an infinite planning horizon maximises the expectation of an additively separable concave utility function:<sup>4</sup>

$$\text{Max}_{Q_{jt}} E_t U_t = \sum_{i=0}^{\infty} \beta^i E_t u(C_{t+i}) \quad j=1,2 \quad (3.8)$$

where  $\beta \equiv 1/(1+\delta)$  and  $\delta$  is the subjective rate of time preference.  $C_t$  is consumption at time  $t$  of a single good whose units represent the numeraire of the model. Hence  $\beta$  is the price of units of  $C_{t+1}$  in terms of units of  $C_t$ .

Assume that the representative agent consumes part of current wealth  $A_t$  and invests the rest  $A_t^* = A_t - C_t$  in the two assets. His budget constraint becomes:

$$\begin{aligned} A_{t+1} &= A_t^* [\theta_t(1+r_t) + (1-\theta_t)(1+r^*)] \\ &= Q_{1t}(1+r_t) + Q_{2t}(1+r^*) \end{aligned} \quad (3.9)$$

where  $Q_{1t} = A_t^* \theta_t$  and  $Q_{2t} = A_t^* (1-\theta_t)$  are the amounts of current wealth invested in the risky and riskless asset respectively. Notice that, if  $\theta_t=1$ , (3.9) becomes  $A_{t+1} = (A_t - C_t)(1+r_t)$ . Defining  $N_t$  as the number

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4. Different versions of the Consumption Capital Asset Pricing Model can be found, inter alia, in Lucas (1978), Grossman and Shiller (1981), LeRoy and La Civita (1981), Brock (1982), Michener (1982), Hansen and Singleton (1983), Sargent (1987), Ch. 3.

of shares held by the representative consumer at the beginning of time  $t$ , we have  $A_t = (P_t + D_t)N_t$  and therefore  $A_{t+1}/P_t = (1+r_t)N_{t+1}$ . Hence (3.9) becomes:

$$C_t + P_t N_{t+1} = (P_t + D_t)N_t \quad (3.10)$$

which is the form of the budget constraint adopted in Lucas (1978) and Sargent (1987, Ch.3). Notice that, as in the previous model, with one market portfolio,  $N_{t+1} = N_t = 1$ . Hence under market clearing (3.10) implies  $C_t = D_t$ , i.e. consumption demand equals the supply of the consumption good distributed by the representative firm.

The Euler equations of the problem can be obtained by substituting for  $C_t$  and  $C_{t+1}$  in the objective function using the constraint (3.9) and setting the first derivative of  $E_t U_t$  with respect to  $Q_{1t}$  equal to zero.<sup>5</sup> By definition:

$$C_t = A_t - A_t^* = A_t - Q_{1t} - Q_{2t}$$

$$C_{t+1} = A_{t+1} - A_{t+1}^* = Q_{1t}(1+r_t) + Q_{2t}(1+r_t^*) - Q_{1t+1} - Q_{2t+1}$$

Hence, the first-order conditions are given by:

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5. In the maximisation problem of Section II current wealth was entirely invested in the two assets, thus maximising with respect to  $\Theta_t A_t$  and  $(1-\Theta_t)A_t$  was the same as maximising with respect to  $\Theta_t$ . In the present model, however, part of current wealth is consumed, and only the remaining part  $A_t^*$  is invested. It follows that the control variables of the problem must be  $Q_{1t} = \Theta_t A_t^*$  and  $Q_{2t} = (1-\Theta_t)A_t^*$ , since  $\sum Q_{jt} = A_t^*$ .

$$\partial E_t U_t / \partial Q_{1t} = - E_t u'(C_t) + \beta E_t [u'(C_{t+1})(1+r_t)] = 0$$

$$\partial E_t U_t / \partial Q_{2t} = - E_t u'(C_t) + \beta E_t [u'(C_{t+1})(1+r^*)] = 0$$

and therefore:

$$u'_t = \beta E_t [u'_{t+1}(1+r_t)] = \beta E_t [u'_{t+1}(1+r^*)] \quad (3.11)$$

where  $u'_t \equiv u'(C_t)$ . Since  $C_t$  is known at time  $t$ , we can divide both sides of (3.11) by  $u'_t$  and obtain:

$$\begin{aligned} 1 &= E_t [(\beta u'_{t+1} / u'_t)(1+r_t)] = E_t [(\beta u'_{t+1} / u'_t)(1+r^*)] \\ &= E_t [S_{t+1}(1+r_t)] = E_t [S_{t+1}(1+r^*)] \end{aligned} \quad (3.12)$$

where  $S_{t+1} \equiv \beta u'_{t+1} / u'_t$  is the marginal rate of intertemporal substitution between consumption at time  $t+1$  and consumption at time  $t$ . From (3.12):<sup>6</sup>

$$E_t(1+r_t) = (E_t S_{t+1})^{-1} [1 - \text{Cov}_t(S_{t+1}, r_t)] \quad (3.13)$$

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6. Notice that the second equation in (3.13) coincides with Hall's random walk model of consumption, which is of course crucially dependent of the assumed constancy of the real interest rate  $r^*$ .

$$1+r^* = (E_t S_{t+1})^{-1}$$

and therefore:

$$\pi_t = - (1+r^*) \text{Cov}_t(S_{t+1}, r_t) \quad (3.14)$$

Equation (3.14) expresses the risk premium  $\pi_t$  as a function of the riskiness of the market portfolio, as defined by the negative covariance of its return with the marginal rate of intertemporal substitution. Let us compare (3.14) with (3.4). In the previous model, asset riskiness was simply defined as the conditional variance of the asset return. As such, it was exogenously given and had to be left unexplained. In the present model, on the other hand, asset riskiness is equal to the covariance between the risky return and the marginal rate of intertemporal substitution, and is thus explained by the model. Notice that the conditional covariance in (3.13) and (3.14) is typically non positive. Utility maximisation implies that the representative consumer will try to smooth consumption over time by varying the required rate of return on the risky asset. If the present level of consumption is unusually low (which, given the concavity of the utility function, implies a low  $S_{t+1}$ ) the consumer tends to dissave and sell assets in order to increase consumption. Thus, in order to bring desired savings back in line with actual savings, returns must increase. The higher is the negative covariance

between an asset return and the marginal rate of intertemporal substitution, the higher is the amount of that asset which the consumer sells in periods of low consumption. The opposite is true when  $C_{t+1}$  is low relative to  $C_t$ . Hence the conditional covariance is a measure of asset riskiness. If an asset return has zero covariance with the marginal rate of intertemporal substitution, the expected return on that asset will be  $r^* = (E_t S_{t+1})^{-1} - 1$ . The higher the covariance (in absolute terms), the higher will be the expected return and thus the risk premium above the minimum expected return  $r^*$ .

Notice also that, from the definition of  $r_t$ , (3.11) can be written as:

$$u'_t P_t = \beta E_t [u'_{t+1} (P_{t+1} + D_{t+1})] \quad (3.15)$$

The stochastic difference equation (3.15) is equivalent to equation (1.3) and represents the equilibrium condition of the model. The condition can be interpreted as follows: the left-hand side is the marginal cost, in terms of foregone consumption, from the purchase of a share in the market portfolio. In equilibrium this equals the right-hand side, which represents the benefit, in terms of future consumption, deriving from holding the share (capital value plus dividends). As in Chapter 1, by forward recursive substitution of (3.15) we obtain:

$$P_t = P_t^F = \sum_{i=1}^{\infty} \beta^i E_t[(u'_{t+i}/u'_t)D_{t+i}] \quad (3.16)$$

subject to the transversality condition

$$\lim_{i \rightarrow \infty} \beta^i E_t[(u'_{t+i}/u'_t)P_{t+i}] \quad (3.17)$$

Equation (3.16) gives the bubbleless solution of the model. Clearly, prices still reflect fundamental information about future dividends. However, current and expected consumption, by affecting the covariance measure of asset riskiness, will also have an influence on prices. This can be more clearly seen by rewriting (3.16) as:

$$P_t^F = \sum_{i=1}^{\infty} E_t(S_{t+i}D_{t+i}) \quad (3.18)$$

$$= \sum_{i=1}^{\infty} (1+r^*)^{-i} E_t D_{t+i} + \sum_{i=1}^{\infty} \beta^i \text{Cov}_t[(u'_{t+i}/u'_t), D_{t+i}]$$

where  $S_{t+i} \equiv \beta^i u'_{t+i}/u'_t$  is the marginal rate of intertemporal substitution between consumption at time  $t+i$  and consumption at time  $t$ , and  $\sum \beta^i \text{Cov}_t[(u'_{t+i}/u'_t), D_{t+i}]$ , the sum of conditional covariances

between successive marginal rates of intertemporal substitution and dividends, is the ultimate consumption-based risk measure.

Notice also that  $\pi_t > 0$  if  $\text{Cov}_t(S_{t+1}, r_t) < 0$ . As in the previous model, the martingale restriction for  $r_t$  does not hold in general, unless  $\pi_t$  is constant. This will be true if  $\text{Cov}_t(S_{t+1}, r_t)$  is constant, say equal to  $-\psi$ . In this case,  $\pi_t = (1+r^*)\psi$ ,  $1+\lambda_t = (1+r^*)(1+\psi)$  and therefore:

$$P_t = \sum_{i=1}^{\infty} [(1+r^*)(1+\psi)]^{-i} E_t D_{t+i} \quad (3.19)$$

Hence the martingale restriction (1.6) and the FVM hold, with  $r \approx r^* + \psi$  re-interpreted as a risk-adjusted constant expected rate of return. Again, the constancy of  $\pi_t$  depends on the shape of the utility function, as represented by the ratio  $u'_{t+1}/u'_t$ . In particular,  $\pi_t = 0$  if  $\text{Cov}_t(S_{t+1}, r_t) = 0$ . Hence risk neutrality is still a sufficient (but not necessary) condition for a zero risk premium. In this case,  $u'_{t+1}/u'_t = 1$ , hence  $\text{Cov}_t(S_{t+1}, r_t) = 0$  and, from (3.13),  $\lambda_t = r^* = \delta$ , the subjective rate of time preference.

In order to solve the model analytically, a particular form for the utility function  $u_t$  must be assumed. Again, we distinguish between constant absolute and constant relative risk aversion.

i) Under CARA, the utility function has the following general form (up to an affine transformation):

$$u_t = - \exp(-k^A C_t) \quad (3.20)$$

where  $k^A$  is the CARA parameter. It follows that:

$$P_t^F = \sum_{i=1}^{\infty} \beta^i E_t \{ [\exp(-k^A (C_{t+i} - C_t))] D_{t+i} \} \quad (3.21)$$

ii) Under CRRA, the utility function has the general form:

$$u_t = C_t^{1-k^R} / (1-k^R) \quad (3.22)$$

where  $k^R$  is the CRRA parameter. Then:

$$P_t^F = \sum_{i=1}^{\infty} \beta^i E_t [(C_{t+i}/C_t)^{-k^R} D_{t+i}] \quad (3.23)$$

A workable version of (3.23) can be derived under the assumptions  $\theta_t=1$  and  $k^R=1$ . The latter corresponds to the logarithmic utility function  $u_t=\ln C_t$ . Remember from (3.10) that market clearing requires  $C_t=D_t$ . Hence (3.23) becomes:

$$P_t^F = \sum_{i=1}^{\infty} \beta^i E_t D_t = [\beta/(1-\beta)] D_t \quad (3.24)$$

and therefore:

$$1+r_t = \beta^{-1} D_{t+1}/D_t \quad (3.25)$$

Using this version of the consumption CAPM, Balvers et al. (1990) demonstrate that stock market efficiency is consistent with the presence of a negative relationship between current expected returns and lagged output. To this purpose, they extend the model to include a representative firm, whose objective is to choose the level of investment  $I_t=Y_t-C_t=Y_t-D_t$  as to maximise the present value of shareholders' wealth, as represented by the discounted sum of future dividend payments:

$$\text{Max } E_t \sum_{i=0}^{\infty} \left[ \prod_{j=0}^i (1+r_{t+j-1})^{-1} \right] D_{t+i} \quad (3.26)$$

(with  $r_{t-1}=0$ ). Output  $Y_t$  is produced by a decreasing returns stochastic Cobb-Douglas technology  $Y_t=\mu\nu^t\theta_tK_t^\alpha$ , with capital  $K_t$  as the only input, whose productivity increases over time through technical progress ( $\alpha<1$ ,  $\mu,\nu>0$ ). Production uncertainty is represented by the multiplicative disturbance  $\theta_t$ , which is assumed to be serially uncorrelated and such that  $E(\theta_t)=1$ . In addition, the level of investment  $I_t$  is assumed to be equal to next period capital  $K_{t+1}$ . This corresponds to a time-to-build capital assumption, which

implies the existence of a one period gestation lag before investment becomes productive as capital. For simplicity, full depreciation of capital is assumed in each period. Substituting for  $D_t = \mu \nu^t \theta_t K_t^\alpha - K_{t+1}$  in (3.26) and differentiating with respect to  $K_{t+1}$  we obtain:

$$E_t[(1+r_t)^{-1} \alpha(Y_{t+1}/K_{t+1})] = 1 \quad (3.27)$$

which is the stochastic Euler equation equivalent to (3.12). The general equilibrium solution of the model is then obtained in customary fashion through the method of undetermined coefficients. The proposed solution is  $K_{t+1} = \alpha \beta Y_t$ , which implies  $D_t = Y_t - K_{t+1} = (1 - \alpha \beta) Y_t$  and, from (3.25):

$$1+r_t = \beta^{-1} Y_{t+1}/Y_t \quad (3.28)$$

Substituting (3.28) in (3.27) proves that the solution is indeed correct. Also, the solution implies:

$$Y_{t+1} = \mu \nu^{t+1} \theta_{t+1} (\alpha \beta)^\alpha Y_t^\alpha \quad (3.29)$$

i.e. autocorrelation in output. It follows that equations (3.28) and (3.29) together imply return predictability: since current returns depend on next period output relative to current output, and output is autocorrelated, then current returns can be predicted on the basis

of available information. Such predictability is however consistent with efficiency, since in the model higher expected returns are exactly offset by a less smooth consumption pattern. It follows that: 1) a rejection of the martingale restriction (1.6) on the basis of (3.28)-(3.29) would not constitute a rejection of the EMT; 2) If other lagged variables are found to be significantly correlated with current returns, it is possible that they may be simply mirroring the correlation between expected returns (or risk premia) and lagged output. One consequence of this, which we shall examine in Chapters 4 and 6, is that, under efficiency, the significance of lagged variables would not survive the inclusion of lagged output among the regressors.<sup>7</sup>

The possibility that the additional degree of variability introduced by variable risk premia and discount rates could justify the excess volatility results delivered by early variance bound tests explains why models of the kind analysed in this section have been raising a growing interest among economists. However, early results did not seem to match the size of the efforts. The common finding, based on the consumption CAPM, has been that the additional degree of variability due to changing discount rates does not help clarify the controversial nature of the variance bound evidence, as we shall see

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7. Cochrane (1990) presents a similar production CAPM model, but uses a different capital accumulation rule, based on an adjustment cost investment function of the type  $K_{t+1} = g(K_t, I_t)$ . The model implies the existence of a negative relationship between current stock returns and lagged investment/capital ratios, which can be tested on the same lines as in Balvers et al..

in the next chapter. On the other hand, recent regression tests based on the consumption CAPM (extended to cover production, as we have just examined) seem to suggest that the predictability of risk premia may be explained in terms of output correlatedness, thus providing empirical support for the attempt to salvage the EMT within a more comprehensive setting. We shall examine such evidence in Chapters 4 and 6.

#### IV. Rational Bubbles.

Another possible extension of the constant discount rate FVM is widely explored in the rational bubbles literature. In the financial world the term 'speculative bubble' has been often associated with dramatic variations in stock prices over the short to medium term which cannot be easily explained by identifiable changes in fundamentals. In particular, the term has been employed to denote a number of turbulent historical episodes in which stock and commodity prices appeared to be driven by the 'madness of crowds' engaged in chaotic speculative flurries more than by the rational evaluation of fundamentals.<sup>8</sup>

The theory of rational bubbles has very little to do with such manias and panics. Rational bubbles are defined in the context of the

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8. See, e.g., Kindleberger (1978), Malkiel (1985) and Garber (1990) for an historical account of these events.

EMT examined in Chapter 1 and share the essential properties of the FVM. Remember in Chapter 1 we saw that the general solution to the stochastic difference equation (1.3), representing the stock market equilibrium condition, was the sum of a fundamental component  $P_t^F$  and of a rational bubble  $B_t^*$  (equation (1.4)). We also said that, if the probability of boundless growth in  $P_t$  is not zero, the rational bubble  $B_t^*$  is ruled out by imposing the transversality condition (1.5). If, however, bound growth is almost certain (i.e. the event of boundless growth is discarded by investors), or the transversality condition does not hold, stock prices will not reflect fundamental valuations, as they will also be driven by the rational bubble component  $B_t^*$ . We call  $B_t^*$  a bubble because it represents a deviation from the fundamental price  $P_t^F$ . But rational bubbles carry certain additional features which differentiate them from all other kinds of speculative bubbles and imply several restrictions on their possible forms.

Before we examine these restrictions, however, it should be noticed that the martingale process  $B_t$  - and the bubble  $B_t^*$  itself - are very mysterious objects indeed. Under Rational Expectations, the existence of  $B_t^*$  reveals a self-fulfilling belief that  $P_t$  is affected by non fundamental variables, or at least by fundamental variables in a way which differs from the prediction of the FVM. The presence of  $B_t^*$  makes  $P_t$  diverge from  $P_t^F$ , but the theory of rational bubbles provides no explanation for such a divergence, nor does it identify

variables which could have an influence on  $B_t^*$ . A rational bubble can thus be literally anything, and restrictions on its form do not derive from an investigation of the underlying phenomena which would establish the existence of a bubble, but only from the properties of the mathematical model in which bubbles are defined. Notice that, as an additional component of stock prices beyond market fundamentals, a rational bubble resembles the 'noise' variable in equation (2.38). However, unlike noise, rational bubbles are subject to several theoretical restrictions, which imply a highly specialised shape.<sup>9</sup>

The most important restriction on a rational bubble - one which clearly separates bubbles from noise - is that a bubble is an explosive stochastic process, since by definition:

$$E_t B_{t+1}^* = \beta^{-1} B_t^* \quad (3.30)$$

As  $\beta$  is smaller than one,  $B_t^*$  has an explosive conditional expectation and therefore grows without bound along a stochastic exponential trend at the rate  $\delta$ , equal to the subjective rate of time preference. Also, from (3.30):

$$E_t B_{t+i}^* = \beta^{-i} B_t^* \quad (3.31)$$

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9. The following analysis draws from Diba and Grossman (1988a,b). See also Obstfeld and Rogoff (1986) and, for a recent review of the rational bubbles literature, Flood and Hodrick (1990).

i.e. the expected value of a rational bubble at any future date  $t+i$  is a geometric multiple of its current value. Equation (3.30) also implies:

$$B^*_{t+1} = \beta^{-1}B^*_t + z_{t+1} \quad (3.32)$$

where  $z_{t+1}$  is an innovation process with  $E_t z_{t+1} = 0$ . Solving (3.32) backwards gives:

$$B^*_t = \beta^{-t}B^*_0 + \sum_{i=0}^{t-1} \beta^{-i} z_{t-i} \quad (3.33)$$

where  $B^*_0$  is the bubble on the first date of trading of the share. Equation (3.33) shows that past innovations have a growing effect on current bubbles, which is proportional to their distance in time.

The explosive nature of rational bubbles is at the origin of a second fundamental restriction on their form. Since  $B^*_t$  is a component of  $P_t$ , explosivity implies that the current price itself is expected to increase or decrease without bound in the future, according to whether the bubble is positive or negative. But since prices which are set on a negative exponential trend are expected to become negative at a finite future date, it follows that investors' demand for shares whose price contains a negative bubble is equal to

zero. Given free disposal of shares, this implies that rational bubbles cannot be negative. Hence, from (3.32):

$$z_{t+1} \geq -\beta^{-1} B_t^* \quad (3.34)$$

From (3.34), if  $B_t^* = 0$  then  $z_{t+1}$  must be nonnegative. But since by definition the conditional expectation of  $z_{t+1}$  is zero, this means that  $z_{t+1}$  equals zero with probability one. This brings us to a third restriction on the structure of rational bubbles: if a bubble equals zero at time  $t$ , then it will be zero at any subsequent date. By a recursive argument, this implies that the bubble can only start at time 0, on the first day of the share trading, and that, if the bubble disappears after that date, it cannot start again. Also, since  $B_0^* \geq 0$ , it follows that  $E_{-1} B_0^*$  cannot equal zero. Therefore, if a bubble starts at date 0, it must have been anticipated prior to quotation.

Rational bubbles are thus explosive, nonnegative and non-recurring stochastic processes, which drive up stock prices on a stochastic exponential trend from the first date of quotation. Of course, stock prices have never and are very unlikely to ever experience such perpetual growth, and this is why it is quite plausible to impose the transversality condition (1.5) on the solution (1.4).<sup>10</sup> In fact rational bubbles can be empirically

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10. Benveniste and Scheinkman (1982) demonstrate that the transversality condition is implied by the optimising behaviour of the representative investor.

significant phenomena only insofar as they have a zero probability of boundless increase. The transversality condition rules out rational bubbles only if the event of boundless growth has positive probability. If, on the other hand, the bubble is almost surely bound to burst in a finite time, rational bubbles are possible even under (1.5). This will be the case if the innovation  $z_{t+1}$  has the following form:

$$z_{t+1} = (\gamma_{t+1} - \beta^{-1})B_t^* + \phi_{t+1} \quad (3.35)$$

where  $\gamma_t$  and  $\phi_t$  are mutually and serially independent random variables with  $E_t \gamma_{t+1} = \beta^{-1}$  and  $E_t \phi_{t+1} = 0$ . Substituting in (3.32) gives:

$$B_{t+1}^* = \gamma_{t+1}B_t^* + \phi_{t+1} \quad (3.36)$$

From (3.36), the bubble bursts if the event  $\gamma_{t+1}=0$  occurs. Hence, assuming that the event has positive probability  $p$ , the probability that the bubble will not burst by date  $T > t$ , which is equal to  $(1-p)^{T-t}$ , tends to zero as  $T$  tends to infinity. Thus the bubble will burst almost surely.

Now imagine that the event  $\gamma_{t+1}=0$  occurs and the bubble bursts. Then from (3.36), in case of a positive realisation of  $\phi_{t+1}$ , a new independent bubble would immediately start. However, we know that

rational bubbles can only start at the first date of trading and that, once burst, they cannot start again at a later date. This property derives from equation (3.31), and is thus quite independent of the particular process (3.35) for the innovation  $z_{t+1}$ . Under (3.35), the nonnegativity of rational bubbles would imply that the event  $\gamma_{t+1}=0$  could not coincide with a negative realisation of  $\phi_{t+1}$ . Accordingly, since the event has positive probability and  $\gamma_{t+1}$  and  $\phi_{t+1}$  are independent,  $\phi_{t+1}$  must be nonnegative. This, combined with the fact that  $E_t\phi_{t+1}=0$ , means that  $\phi_{t+1}$  is zero with probability one. Hence we conclude that rational bubbles which come and go are incompatible with nonnegativity and thus must be ruled out, even if a zero probability of infinite growth would allow their existence under the transversality condition.

The above analysis provides a powerful argument for ruling out the presence of rational bubbles in the process generating stock prices on purely theoretical grounds. Another theoretical argument to the same purpose has been presented by Evans (1985, 1989a), on the basis of an analysis of the stability of rational expectations equilibria under a natural learning rule. Recently, Evans (1989b) has criticised the arguments of Diba and Grossman against rational bubbles by pointing out that, even if these bubbles cannot come and go (i.e. burst) over time, it is still possible that they periodically collapse, i.e. shrink to lower values, without disappearing. Evans gives the following example of such a bubble:

$$\begin{aligned}
 B^*_{t+1} &= \beta^{-1} B^*_t \zeta_{t+1} & \text{if } B^*_t \leq b \\
 B^*_{t+1} &= [\delta + (p\beta)^{-1} \theta_{t+1} (B^*_t - \beta\delta)] \zeta_{t+1} & \text{if } B^*_t > b
 \end{aligned} \tag{3.37}$$

where  $\delta, b > 0$ ,  $\delta < \beta^{-1}b$ ,  $\zeta_{t+1}$  is a multiplicative disturbance with  $E_t \zeta_{t+1} = 1$  and  $\theta_{t+1}$  is an independently and identically distributed Bernoulli process which equals one with non zero probability  $p$  and zero with probability  $1-p$ . Hence (since  $E_t \theta_{t+1} = p$ ), both equations in (3.37) satisfy (3.30). Also, if  $B^*_t > 0$  then  $B^*_s > 0$ , for all  $s > t$ . Notice that the second equation in (3.37) reduces to (3.36) (with a multiplicative disturbance) for  $\delta = 0$ , while it reduces to the first equation in (3.37) as  $p$  tends to 1. The bubble in (3.37) grows at mean rate  $\beta^{-1}$  as long as  $B^*_t \leq b$ . But as soon as  $B^*_t > b$  the bubble starts growing faster at mean rate  $(\beta p)^{-1}$ , until it collapses to  $\delta$ , which it does with probability  $1-p$ , and then starts growing again at rate  $\beta^{-1}$ .

Hence, despite the existence of specific theoretical restrictions on rational bubbles, the possibility of periodically collapsing bubbles consistent with such restrictions leaves the question open about whether bubbles of this kind are present in stock prices. As we shall see in the next chapter, the available empirical evidence against rational bubbles is also weakened as a result of the possibility of collapsing bubbles.

## CHAPTER 4

### TESTING FOR THE EXTENDED FVM

#### I. Variable risk premia.

As pointed out in the previous chapter, general equilibrium models allowing for variable risk premia provide a possible route for an explanation of the empirical evidence presented in the 'excess' volatility literature. Despite the non stationarity issue surrounding variance bound tests, the aim of this line of research is to observe a reduction in variance ratios below their unity benchmark, in the hope that this would end the 'excess' volatility debate and reconduct the FVM - suitably extended to account for variable expected returns - under the protective umbrella of the EMT paradigm.

The first attempt in this direction has been made by Grossman and Shiller (1981),<sup>1</sup> who have employed the Consumption CAPM examined in the previous chapter to allow consumption smoothing to increase

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1. Pesaran (1989) presents similar results.

the variability of the ex post price  $P_t^*$ . In this case we have, from (3.16):

$$P_t^* = \sum_{i=1}^{\infty} \beta^i [(u'_{t+i}/u'_t)D_{t+i}] \quad (4.1)$$

and from (3.15):

$$P_t^* = S_{t+1}(P_{t+1}^* + D_{t+1}) \quad (4.2)$$

which, by forward recursive substitution, yields:

$$P_t^* = \sum_{i=1}^{T-t} \beta^i [(u'_{t+i}/u'_t)D_{t+i}] + S_{T-t}P_T^* \quad (4.3)$$

It follows that the series for  $P_t^*$ , calculated recursively from (4.2), will present an additional degree of variability due to variations in the marginal rate of intertemporal substitution  $S_{t+1}$ , which remains unchanged in the constant discount rate FVM. As in the latter, we can use the approximation  $P_T^* = P_T$  to calculate a time series for  $P_t^*$ . However, rather than assuming a value for the constant discount rate  $r$ , we need to specify a particular form for the utility function and define values for its parameters. Under the Constant Relative Risk Aversion utility function (3.22), (4.2) becomes:

$$P_t^* = \beta (C_{t+1}/C_t)^{-k^R} (P_{t+1}^* + D_{t+1}) \quad (4.4)$$

Hence, given values for the parameters  $\beta$  and  $k^R$ , variations in the growth rate of per capita consumption will generate additional variation in  $P_t^*$ , thereby increasing  $\text{Var}(P_t^*)$ .

Empirical results based on this approach have not been particularly successful. The typical outcome, based on US data, is that variations in expected returns are not nearly as large as they should be in order to drive price variance ratios below unity. It turns out that this same conclusion can be drawn from our Italian sample. We assume a CRRA utility function and calculate  $P_t^*$  as in (4.4). Consumption is measured as Private Per Capita Final Consumption Expenditure at constant prices.<sup>2</sup> Results are reported in Table 4.1, where variance ratios dependent on  $P_t^*$  are reported under constant and variable discount rates (assuming a value of 0.98 for the discount factor  $\beta$  and 1 for the coefficient of relative risk aversion). As can be seen from the table and in Figures 4.1-4.4, although Shiller's price variance ratio does decline under variable discount rates, the decline is not sufficient to drive the ratio below unity, except for implausibly high values of the coefficient of

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2. See Data Appendix for a description of the consumption series.

| TABLE 4.1 - VARIANCE BOUND TESTS |     |
|----------------------------------|-----|
| 1                                | 2   |
| 3                                | 4   |
| 5                                | 6   |
| 7                                | 8   |
| 9                                | 10  |
| 11                               | 12  |
| 13                               | 14  |
| 15                               | 16  |
| 17                               | 18  |
| 19                               | 20  |
| 21                               | 22  |
| 23                               | 24  |
| 25                               | 26  |
| 27                               | 28  |
| 29                               | 30  |
| 31                               | 32  |
| 33                               | 34  |
| 35                               | 36  |
| 37                               | 38  |
| 39                               | 40  |
| 41                               | 42  |
| 43                               | 44  |
| 45                               | 46  |
| 47                               | 48  |
| 49                               | 50  |
| 51                               | 52  |
| 53                               | 54  |
| 55                               | 56  |
| 57                               | 58  |
| 59                               | 60  |
| 61                               | 62  |
| 63                               | 64  |
| 65                               | 66  |
| 67                               | 68  |
| 69                               | 70  |
| 71                               | 72  |
| 73                               | 74  |
| 75                               | 76  |
| 77                               | 78  |
| 79                               | 80  |
| 81                               | 82  |
| 83                               | 84  |
| 85                               | 86  |
| 87                               | 88  |
| 89                               | 90  |
| 91                               | 92  |
| 93                               | 94  |
| 95                               | 96  |
| 97                               | 98  |
| 99                               | 100 |

| VARIANCE RATIOS                  |        |                            |                            |
|----------------------------------|--------|----------------------------|----------------------------|
|                                  |        | Constant<br>Discount rates | Variable<br>Discount rates |
| 981b), EQ. (2.11):               |        | 5.11                       | 2.63                       |
| 1986b), EQ. (2.27):              | k=1    | 0.30                       | 0.30                       |
|                                  | k=2    | 0.62                       | 0.62                       |
|                                  | k=5    | 0.91                       | 0.93                       |
|                                  | k=10   | 1.67                       | 1.68                       |
| 1987), EQ. (2.30):               |        | 1.19                       | 2.73                       |
| (1989), EQ. (2.31):              |        | 0.33                       | 0.32                       |
| 983b), EQ. (2.37):               |        | 3.10                       | 1.57                       |
| Discount rate =                  | 4.675% |                            |                            |
| Discount Rate: Discount Factor = | 0.98   |                            |                            |
| CRRA =                           | 1      |                            |                            |

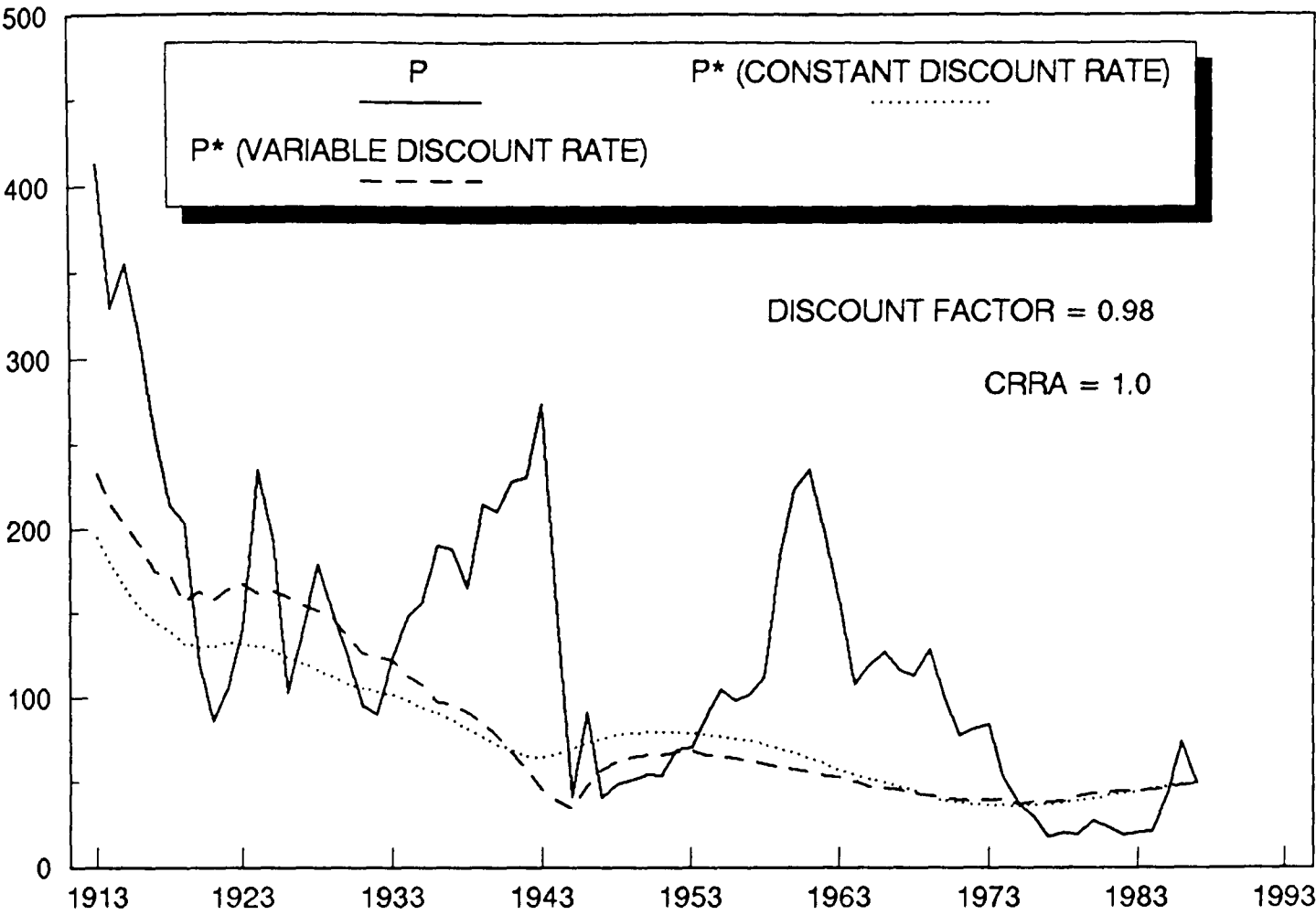
ce: Banca d'Italia Index for December, deflated by CPI  
a Private Consumption, Constant Prices, ISTAT  
913 - 1987

TABLE 4.1 - VARIANCE BOUND TESTS

| VARIANCE RATIOS                                |      |                            |                            |
|------------------------------------------------|------|----------------------------|----------------------------|
|                                                |      | Constant<br>Discount rates | Variable<br>Discount rates |
| MILLER (1981b), EQ. (2.11):                    |      | 5.11                       | 2.63                       |
| LEIDON (1986b), EQ. (2.27):                    | k=1  | 0.30                       | 0.30                       |
|                                                | k=2  | 0.62                       | 0.62                       |
|                                                | k=5  | 0.91                       | 0.93                       |
|                                                | k=10 | 1.67                       | 1.68                       |
| ROY AND PARKE (1987), EQ. (2.30):              |      | 1.19                       | 2.73                       |
| SARAN (1989), EQ. (2.31):                      |      | 0.33                       | 0.32                       |
| EST (1988b), EQ. (2.37):                       |      | 3.10                       | 1.57                       |
| Constant Discount rate = 4.675%                |      |                            |                            |
| Variable Discount Rate: Discount Factor = 0.98 |      |                            |                            |
| CRRA = 1                                       |      |                            |                            |

data source: Banca d'Italia Index for December, deflated by CPI  
for Capita Private Consumption, Constant Prices, ISTAT  
period: 1913 - 1987

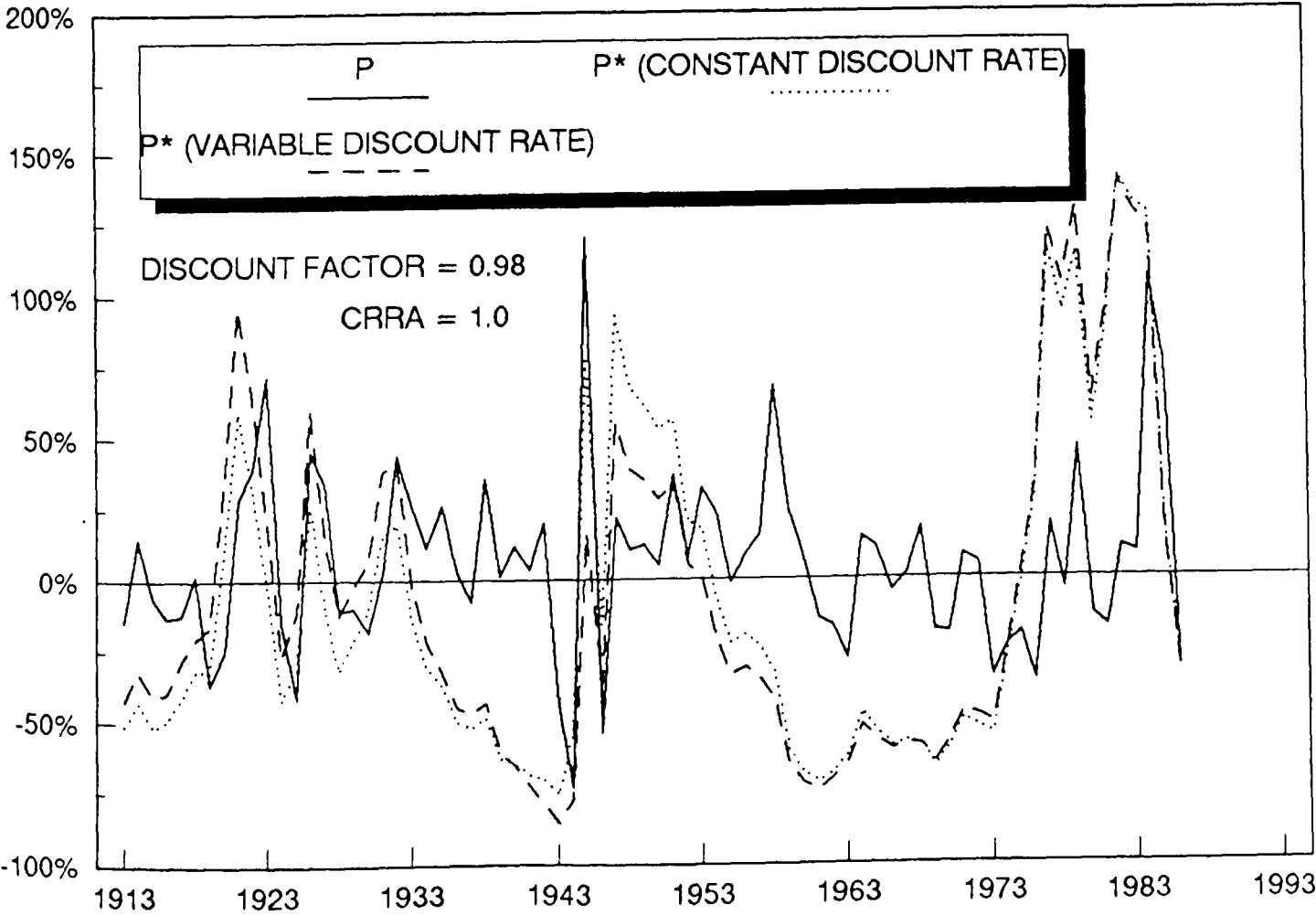
Figure 4.1 REAL PRICE INDEX AND EX POST PRICE



Sources: Banca d'Italia Index, deflated by CPI

Private Per Capita Final Consumption at Constant Prices, ISTAT

Figure 4.2 REAL RETURNS AND EX POST RETURNS



Sources: Banca d'Italia Index, deflated by CPI

Private Per Capita Final Consumption at Constant Prices, ISTAT

Figure 4.3 VARIABLE DISCOUNT RATE (CRRA=1.0)

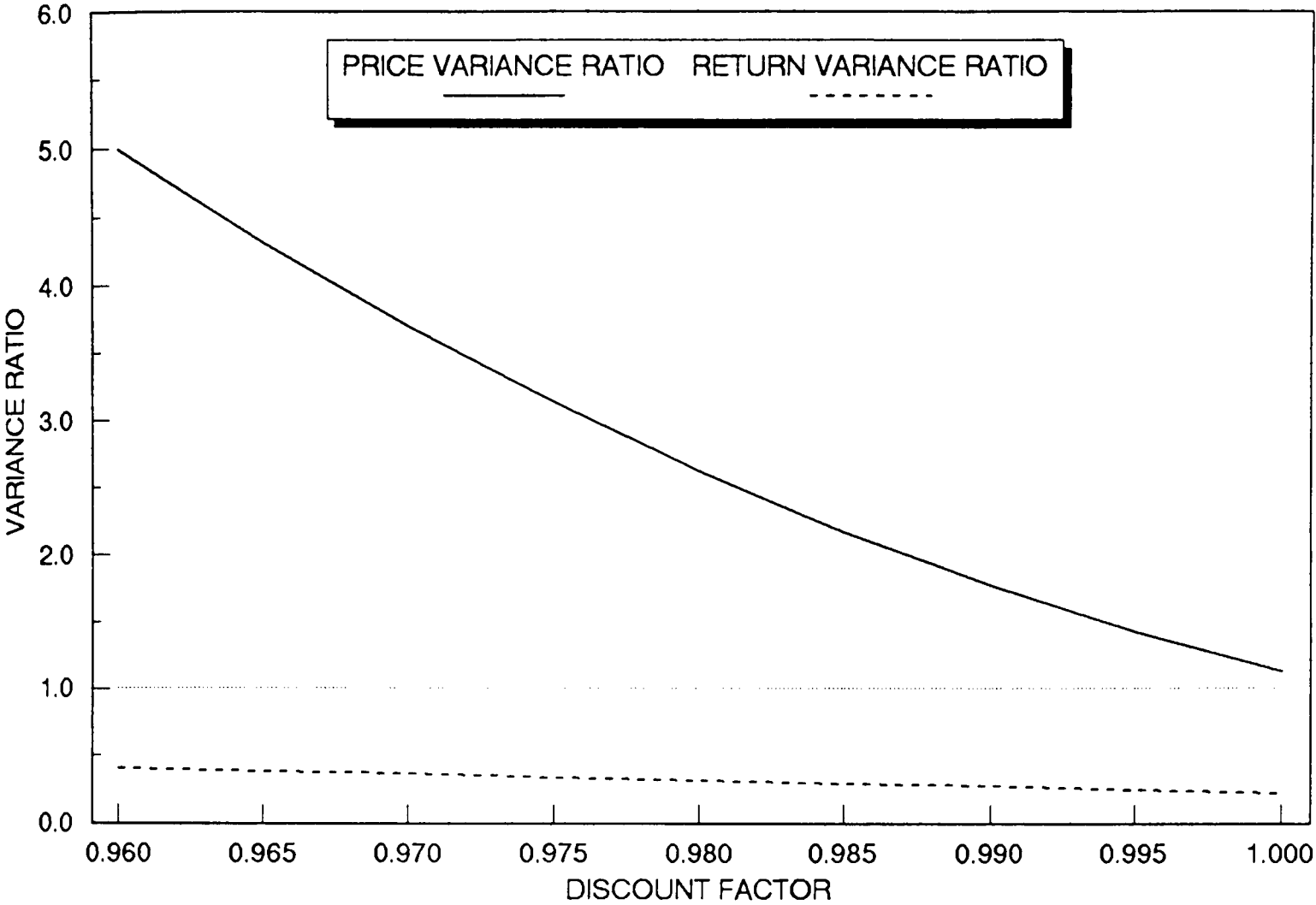
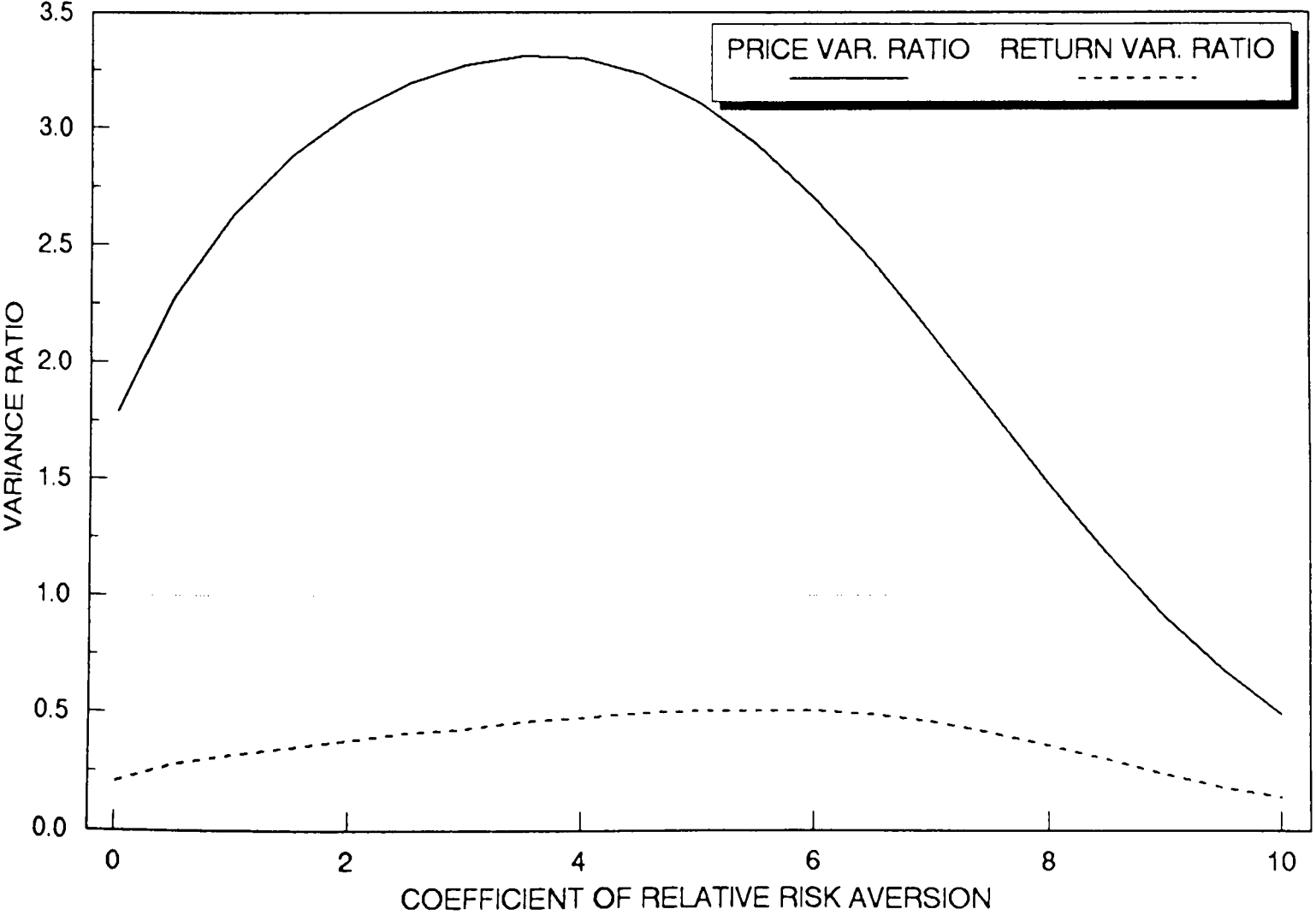


Figure 4.4 VARIABLE DISCOUNT RATE (BETA=0.98)



relative risk aversion.<sup>3</sup> The same is true for West's ratio, while LeRoy and Parke's ratio more than doubles under the new set-up, and actually drives away from near-unity. On the other hand, ratios which were already below one under constant discount rates are only marginally affected by consumption smoothing and, well in accordance with the predictions of the EMT, remain below unity under all possible values of  $\beta$  and  $k^R$ . This can be seen, for Pesaran's return variance inequality (2.35), in Figure 4.2, which shows  $r_t^*$  under consumption smoothing, and Figures 4.3 and 4.4, in which Pesaran's ratio remains below one for all possible values of the discount factor and the CRRA.

Hence results on Italian data seem to confirm that the additional variability injected into the FVM by variable risk premia is not sufficient to resolve the controversy about 'excess' volatility examined in the previous chapter. Rather, the available evidence strengthens the conclusion we reached at the end of Chapter 2, namely that regression tests should be preferred to variance bound tests as a tool to help us discriminate between alternative hypotheses regarding stock market efficiency.

Several attempts have been recently made in this direction. Notably, Fama and French (1988b) and Poterba and Summers (1988) have

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3. This result has an interesting parallel with Mehra and Prescott's (1985) equity premium puzzle, i.e. the empirical observation that the actual excess return of US equities over bonds - equal to an average 8% over the past sixty years - can be made consistent with the consumption CAPM only by assuming a very high CRRA (around 10).

used regression tests to document the existence of a small degree of positive autocorrelation in stock returns over horizons shorter than twelve months and, at the same time, of a more significant degree of negative autocorrelation in returns over a three to five year horizon. Such an autocorrelation pattern suggests the presence of a long run mean reverting component in stock prices, which is obviously inconsistent with the martingale restriction associated with the constant discount rate FVM. Similarly, Fama and French (1988a) and Campbell and Shiller (1988a,b) have shown that the current dividend yield (i.e. the dividend-price ratio) is a significant predictor of future stock returns, and that its significance increases with the return horizon. Clearly, if stock prices have a mean reverting component, scale measures like dividend or earning yields will provide an indication of the current position of prices relative to their average relationship to dividends or earnings. When, for instance, prices are unusually high, scale measures will be unusually low relative to their history and will therefore predict a fall in prices. This should result in a positive relationship between future stock returns and current scale measures.<sup>4</sup> Other variables found to have predictive ability for stock returns include the rate of inflation (Fama and Schwert (1977), Pesaran (1989)), the default spread, i.e. the difference between the corporate bond yield and the

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4. The predictive power of dividend yields was pointed out long ago by Dow (1920) and discussed in Rhea (1932).

Treasury Bill rate (Keim and Stambaugh (1986), Campbell (1987)) and the ex ante volatility of stock returns (French, Schwert and Stambaugh (1987), Attanasio and Wadhwani (1989)). Cutler, Poterba and Summers (1990a) have recently examined the forecasting power of many of these variables for stocks and several other asset categories. Such evidence,<sup>5</sup> which appears in the form of traditional orthogonality tests, is not affected by the stationarity issue which plagues the 'excess' volatility results. However, not unlike the latter, stock returns predictability does not *per se* provide conclusive evidence in favour or against the EMT. As we saw in the previous chapter, predictable stock returns can still be accommodated within a general equilibrium model with variable expected returns, in which stock market efficiency is fully preserved. We have seen, in particular, how Balvers et al. (1990) extend the consumption CAPM to include a representative producer and are able to show that market efficiency is consistent with a negative relationship between current expected returns and lagged output. This implication of the model can actually be tested by taking log transformations of equations (3.28) and (3.29):

$$\ln(1+r_t) = -\ln\beta + \ln Y_{t+1} - \ln Y_t \quad (4.5)$$

$$\ln Y_{t+1} = (\ln\gamma - \eta) + (\ln\nu)t + \alpha \ln Y_t + \epsilon_{t+1} \quad (4.6)$$

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5. We shall explore stock return predictability in more detail in Chapter 6.

where  $\gamma = \mu\nu(\alpha\beta)^\alpha$  and  $\eta$  is chosen such that  $E(\epsilon_{t+1}) = E(\ln\theta_{t+1}) + \eta = 0$ .

Hence:

$$\ln(1+r_t) = (\ln\gamma - \eta - \ln\beta) + (\ln\nu)t + (\alpha-1)\ln Y_t + \epsilon_{t+1} \quad (4.7)$$

In equation (4.7) the log of lagged output has a negative coefficient when regressed on current stock returns, while a time trend has a positive coefficient. Also, the model implies that lagged output and trend help predict current returns only insofar as they predict current output. It follows that a restricted estimate of (4.7) obtained using  $E_t \ln Y_{t+1}$  from the regression of (4.6) should not differ significantly from the unrestricted estimates obtained from (4.7). Lastly, output should be the only lagged variable to have a significant effect on current returns. Therefore, if other lagged variables are found to be significantly correlated with current returns, the model implies that these variables would just be proxying for the output effect, and should therefore disappear once they are used along with lagged output in the same regression model.

Balvers et al. estimate equation (4.7) using monthly, quarterly, 1-, 3- and 5-year returns on US data, and quarterly returns for Japan, United Kingdom and Canada. An index of industrial production is used as a proxy for output. They conclude that the available evidence is broadly in line with the predictions of their model, which appear to be robust to different return horizons and lag

structures, and across countries (see Tables I-III in the paper). In addition, Balvers et al. show that the lagged dividend yield, while significant on its own when regressed against current returns, becomes insignificant when used as an additional regressor in (4.7). Hence they conclude that the dividend yield effect presented in Fama and French (1988a) and Campbell and Shiller (1988a,b) is consistent with market efficiency and cannot be interpreted as evidence against the EMT.<sup>6</sup>

In Table 4.2 we have estimated equation (4.7) on our Italian sample.<sup>7</sup> Unlike variance bound tests, regression tests on Italian

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6. This interpretation is also favoured by Fama and French (1988a), while Campbell and Shiller (1988a,b) and Poterba and Summers (1988) interpret their results as evidence against the EMT. For a critical review on the empirical findings on return predictability, see Kim, Nelson and Startz (1988) and Lo and McKinlay (1988). The dispute has been going on for some time now. Shiller (1984, Table 2, p.490) found evidence of a relationship between stock returns and lagged dividend yields on annual US data, and argued that this result is in contrast with the prediction of the FVM with constant discount rates, where a higher than average dividend yield is associated with an expected capital loss, needed to preserve the constancy of the expected total return. In contrast with this interpretation, Rozeff (1984) showed that, under the Gordon-Shapiro model, the dividend yield approximates the risk premium if dividend growth is assumed constant. Campbell and Shiller (1988a) found little evidence that dividend yields forecast changes in real interest rates or other aspects of risk. However, Attanasio and Wadhvani (1989) have recently argued that, when a GARCH process is used to control for varying expected returns, the dividend yield loses its predictive power (at least in the US). This conclusion is somewhat weakened in Attanasio (1989), who shows that, if the Treasury Bill rate and the inflation rate are added to the dividend yield, the three variables become jointly significant. Finally, in a model similar to Balvers et al., Cochrane (1990) shows that stock returns are negatively correlated with the lagged investment/capital ratio. However, the particular method followed by Cochrane to construct a series for the investment/capital ratio - using an investment series and a quadratic capital accumulation rule with adjustment costs - is extremely sensitive to the particular values assumed for the constant depreciation rate and the adjustment cost parameter. This has an obvious repercussion on the empirical testing of the model. Cochrane finds, however, that the lagged dividend yield remains significant as an additional regressor (see Table III in the paper).

7. See Data Appendix for the source of the Industrial Production Index. Along with coefficients' values and standard errors, each regression equation reports White's Heteroscedasticity Consistent Standard Errors (see White (1980)), t-values (computed on

TABLE 4.2

Equation (4.7)

EQ(1) Modelling  $r_t$  by OLS from 1913 to 1986

| VARIABLE                                                                               | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|----------------------------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                                                                               | 3.149       | 17.896    | 47.715   | .176    | .000          |
| $\ln IP_t$                                                                             | -2.071      | 10.871    | 29.338   | -.190   | .001          |
| TREND                                                                                  | .124        | .497      | 1.234    | .249    | .001          |
| $R^2 = .001 \quad \sigma = 33.048 \quad F(2,71) = .04 \text{ [.9629]} \quad DW = 1.98$ |             |           |          |         |               |

EQ(2) Modelling  $r_t$  by OLS from 1913 to 1986

| VARIABLE                                                                                | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-----------------------------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                                                                                | -21.256     | 18.331    | 50.555   | -1.160  | .019          |
| $\ln IP_t$                                                                              | -21.758     | 11.809    | 25.222   | -1.843  | .046          |
| TREND                                                                                   | 1.367       | .600      | 1.031    | 2.280   | .069          |
| $DY_t$                                                                                  | 8.670       | 2.631     | 2.814    | 3.296   | .134          |
| $R^2 = .135 \quad \sigma = 30.967 \quad F(3,70) = 3.65 \text{ [.0166]} \quad DW = 1.91$ |             |           |          |         |               |

ordinary standard errors) and squared partial correlation coefficients. The squared coefficient of multiple correlation  $R^2$ , the standard error of the regression  $\sigma$ , the F-statistic (with its probability value under the null hypothesis of a zero coefficient vector) and the Durbin-Watson coefficient are included as descriptive statistics of the regression. All regressions have been run on PC-GIVE (Hendry (1989)).

data present results which often differ considerably from those obtained on data for the US and other countries. This fact, which again highlights the superior discriminatory power and informational content of regression tests versus variance bound tests, strengthens our support for the former as a more appropriate tool for investigating possible departures from the EMT. Equation (1) in Table 4.2 shows that the model in (4.7) is strongly rejected on Italian data. Although the coefficient on the log of industrial production has the expected negative sign, the variable has clearly no predictive power for future returns. In addition, equation (2) shows that the dividend yield does have the expected positive sign when added to regressors, while the log of industrial production and the time trend remain insignificant (using heteroscedasticity-corrected standard errors).

Hence there is a substantial difference between results on Italian data and those presented by Balvers et al.. We should also point out, regarding the latter, that the presence of a trend in equation (4.7), which reflects technical progress in the model, is hard to reconcile with historical experience and common sense. Balvers et al. reject the hypothesis of a unit root in the industrial production index (see their equation 1, Table I and Note 9),<sup>8</sup> but

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8. This is actually quite surprising, since the values reported in equation 1, Table I imply a value of Fuller's (1976)  $\tau$  statistic of -2.64 which, contrary to what is stated in note 9, does not reject the null of a unit root in industrial production, even at a 10% level. The unit root hypothesis cannot be rejected on the Italian Industrial Production Index.

seem to neglect the fact that the same hypothesis would unquestionably be rejected on real returns,<sup>9</sup> thus leaving no space for the inclusion of a trend in the return forecasting equation. On the other hand, dropping the trend from the equation would invariably wipe out the coefficient of industrial production, as we shall actually see in Chapter 6. There we shall document the existence of a significant relationship between current stock returns and a group of lagged variables, including dividend yields, on monthly data for the United States, United Kingdom, Japan and Italy. We interpret our results as evidence against the EMT, but it is clear from the above analysis that such a conclusion can only be drawn if those variables are able to resist the inclusion of lagged output among the regressors.

Despite the accumulation of controversial empirical evidence, the exploration of models with variable risk premia is a major endeavour of current academic research in finance. The desire to protect the efficiency hypothesis from the attacks brought to it from various sides is still very strong among academics and indeed motivates the production of interesting and imaginative papers.<sup>10</sup>

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9. See equation (5) in Table 4.3 for a rejection on Italian data. In fact, the case for trendless stationarity in real returns is so strong that we hardly need any testing. However, for the sake of punctiliousness, we run the same test on Standard & Poor's real returns from 1873 to 1987 (using the data reported in Shiller (1989b)). The t-statistic of the lagged return is -9.89.

10. Among the most recent examples, see Attanasio (1989), Cecchetti and Mark (1990) and Cecchetti, Lam and Mark (1990).

However, this is not the line we shall pursue in the sequel of this study. As remarked in Chapter 2, we regard the assumptions of homogeneous information and rational expectations as the key issues on which to concentrate, if we are to come to grips with the available evidence on stock market behaviour. Chapters 5 and 6 are to be seen as a possible prologue to this attempt. Before concluding the present chapter, however, we shall briefly analyse the available empirical evidence about rational bubbles.

## II. Testing for Rational Bubbles.

We have seen in Chapter 3 that the existence of rational bubbles is subject to a series of stringent restrictions, which provide a strong case for ruling out such bubbles on purely theoretical grounds. The case against rational bubbles is somewhat weakened, however, by the possibility that they might periodically collapse, i.e. shrink from time to time to lower values, without disappearing, and then start growing again. As we shall presently see, the empirical evidence against rational bubbles is also weakened by this possibility.

Remember that a rational bubble  $B_t^*$  is an explosive stochastic process. This implies that, differencing (3.32):

$$\Delta B_{t+1}^* = \beta^{-1} \Delta B_t^* + \Delta z_{t+1} \quad (4.8)$$

with  $\beta < 1$ . Hence:

$$(1 - \beta^{-1}L)(1 - L)B_t^* = (1 - L)z_t \quad (4.9)$$

where  $L$  is the lag operator. Therefore, since  $\Delta B_t^*$  follows a non stationary (and non invertible) ARMA process, the existence of a rational bubble in the price generating process implies that  $\Delta P_t = \Delta P_t^F + \Delta B_t^*$  must also be non stationary.

This hypothesis can be tested using Dickey-Fuller tests for unit roots. On this basis, Diba and Grossman (1988a) reject the presence of rational bubbles in the Standard & Poor's price series. Results on Italian data, reported in Table 4.2, are similar to Diba and Grossman's. The first two equations present Dickey-Fuller tests on the price and dividend series. The equations have been augmented with one lag in the dependent variable in order to obtain white noise residuals. Results suggest the presence of a unit root in the two series. For the price equation, a t-value for the lagged price level of -3.43 (-2.69 using the heteroscedasticity-corrected standard error) implies that the null hypothesis of a unit root in the price series cannot be rejected at the 5% level. A low Durbin-Watson coefficient from the OLS regression of the variable on a constant (as suggested by Sargan and Bhargava (1983) and Bhargava (1986)) agrees with the DF result. As for the the dividend equation, the t-value of

TABLE 4.3

Augmented Dickey-Fuller Tests for Unit Roots in  $P_t$ ,  $D_t$ ,  $\Delta P_t$ ,  $\Delta D_t$ ,  $r_t$ .

EQ(1) Modelling  $\Delta P_t$  by OLS from 1915 to 1987

| VARIABLE         | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT         | 45.318      | 17.766    | 19.725   | 2.551   | .086          |
| TREND            | -.477       | .260      | .263     | -1.834  | .047          |
| $P_{t-1}$        | -.235       | .068      | .087     | -3.430  | .146          |
| $\Delta P_{t-1}$ | .193        | .110      | .187     | 1.752   | .043          |

$R^2 = .164$        $\sigma = 34.610$        $F(3,69) = 4.50$  [.0061]       $DW = 1.84$

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,65) = 1.79$  [.1417]

EQ(2) Modelling  $\Delta D_t$  by OLS from 1915 to 1987

| VARIABLE         | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT         | 1.714       | .569      | .524     | 3.011   | .116          |
| TREND            | -.021       | .009      | .008     | -2.255  | .069          |
| $D_{t-1}$        | -.195       | .040      | .040     | -4.928  | .260          |
| $\Delta D_{t-1}$ | .286        | .098      | .179     | 2.921   | .110          |

$R^2 = .375$        $\sigma = 1.096$        $F(3,69) = 13.79$  [.0000]       $DW = 2.11$

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,65) = .91$  [.4635]

DURBIN-WATSON TESTS

$DW(P_t) = .195$        $DW(D_t) = .066$

TABLE 4.3

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|                                                                              |             |           |          |         |               |
|------------------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| EQ(3) Modelling $\Delta^2 P_t$ by OLS from 1915 to 1987                      |             |           |          |         |               |
| VARIABLE                                                                     | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
| CONSTANT                                                                     | -7.874      | 9.313     | 11.398   | -.845   | .010          |
| TREND                                                                        | -.117       | .209      | .208     | .562    | .005          |
| $\Delta P_{t-1}$                                                             | -.884       | .116      | .194     | -7.614  | .453          |
| $R^2 = .454$ $\sigma = 37.177$ $F(2,70) = 29.13$ [.0000] $DW = 1.87$         |             |           |          |         |               |
| LM-Serial Correlation from Lags 1 to 4: $F\text{-Form}(4,66) = 1.35$ [.2611] |             |           |          |         |               |

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|                                                                              |             |           |          |         |               |
|------------------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| EQ(4) Modelling $\Delta^2 D_t$ by OLS from 1915 to 1987                      |             |           |          |         |               |
| VARIABLE                                                                     | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
| CONSTANT                                                                     | -.715       | .329      | .579     | -2.176  | .063          |
| TREND                                                                        | .012        | .007      | .011     | 1.712   | .040          |
| $\Delta D_{t-1}$                                                             | -.702       | .113      | .191     | -6.219  | .356          |
| $R^2 = .356$ $\sigma = 1.266$ $F(2,70) = 19.36$ [.0000] $DW = 1.92$          |             |           |          |         |               |
| LM-Serial Correlation from Lags 1 to 4: $F\text{-Form}(4,66) = 1.53$ [.2047] |             |           |          |         |               |

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|                                                   |  |  |  |  |  |
|---------------------------------------------------|--|--|--|--|--|
| DURBIN-WATSON TESTS                               |  |  |  |  |  |
| $DW(\Delta P_t) = 1.664$ $DW(\Delta D_t) = 1.305$ |  |  |  |  |  |

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TABLE 4.3

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EQ(5) Modelling  $\Delta r_t$  by OLS from 1914 to 1986

| VARIABLE  | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-----------|-------------|-----------|----------|---------|---------------|
| CONSTANT  | .946        | 8.023     | 7.871    | .118    | .000          |
| TREND     | .019        | .185      | .176     | .101    | .000          |
| $r_{t-1}$ | -1.007      | .121      | .241     | -8.342  | .499          |

$R^2 = .499$        $\sigma = 33.238$        $F(2,70) = 34.85$  [.0000]       $DW = 1.97$

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,66) = .14$  [.9657]

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DURBIN-WATSON TEST

$DW(r_t) = 1.913$

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the lagged dividend level is -4.93 (-4.87 using the H.C.S.E.). Hence the Dickey-Fuller test rejects the unit root hypothesis for dividends. At the same time, however, the Durbin-Watson coefficient is extremely low and suggests the presence of a unit root. This disparity of results seems to be entirely attributable to the abnormally high values of the dividend series in the first few years of the sample (see Appendix A.2). In fact, when equations (1) and (2) are regressed over the period 1925-1987, the t-values drop to -3.04

(-2.21 with H.C.S.E.) for prices and to -2.38 (-3.30 with H.C.S.E.) for dividends.

On the other hand, equations (3) and (4) (where no lagged dependent variable has been added to regressors) clearly indicate that the null hypothesis of a unit root in the first difference of prices and dividends can be strongly rejected, even at the 1% level. Finally, equation (5) comfortably supports our earlier claim about the stationarity of the return series.

A similar test for rational bubbles under constant expected returns can be run on the following lines. As we already noticed in Chapter 2 (equation 2.29), the FVM equation (1.7) can be rearranged as:

$$P_t^F - D_t/r = [(1+r)/r] \sum_{i=1}^{\infty} (1+r)^{-i} E_t \Delta D_{t+i} \quad (4.10)$$

Therefore, provided that dividends are stationary in first differences, a linear combination of prices and dividends will be stationary under the FVM, even if prices and dividends themselves are non stationary in levels. In this case prices and dividends are cointegrated, with the cointegrating parameter equal to the inverse of the discount rate  $r$ . If, on the other hand, prices include a rational bubble, the linear combination in (4.7) will be non stationary, and prices and dividends will not be cointegrated.

Table 4.4 presents results on the cointegrating regression for Italian prices and dividends (equation (1)), along with Dickey-Fuller tests for unit roots in the regression residuals (equation (2)). Results suggest a rejection of the unit root hypothesis. This is certainly true for the Cointegrating Regression Durbin-Watson, which is equal to 0.64. The Dickey-Fuller test on the equation residuals also points towards a rejection of the null, although it is interesting to notice that the ordinary t-value on the lagged residual level (-3.70) is much larger than the t-value calculated using the H.C.S.E., which equals -2.68.

The above evidence runs contrary to the hypothesis that the price series contains a non stationary rational bubble term. Notice that the tests are robust to the criticism, pointed out in Hamilton and Whiteman (1985), according to which the detection of rational bubbles cannot be distinguished from the contribution to market fundamentals of variables which are unobservable to the econometrician. As long as the unobserved variables are stationary in first differences, the stationarity of the first difference of stock prices would imply the absence of rational bubbles, even if non stationary first differences would not necessarily be attributable to such bubbles (since they might instead result from non stationary unobservables). However, as we pointed out earlier, the evidence against rational bubbles is indeed undermined by the possibility of periodically collapsing bubbles, as suggested by Evans (1989b). This

TABLE 4.4

Cointegrating regression of prices and dividends.

EQ(1) Modelling  $P_t$  by OLS from 1913 to 1987

| VARIABLE                                                             | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|----------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                                                             | 45.563      | 7.956     | 7.635    | 5.727   | .310          |
| $D_t$                                                                | 13.835      | .994      | .950     | 13.922  | .726          |
| $R^2 = .726$ $\sigma = 45.333$ $F(1,73) = 193.81$ [.0000] $DW = .64$ |             |           |          |         |               |

Dickey-Fuller test on cointegrating regression residuals

EQ(2) Modelling  $\Delta CR_t$  by OLS from 1914 to 1987

| VARIABLE                                                            | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|---------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                                                            | .236        | 8.065     | 9.496    | .029    | .000          |
| TREND                                                               | -.020       | .183      | .174     | -.107   | .000          |
| $CR_{t-1}$                                                          | -.322       | .087      | .120     | -3.704  | .162          |
| $R^2 = .162$ $\sigma = 33.618$ $F(2,71) = 6.86$ [.0019] $DW = 1.78$ |             |           |          |         |               |

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,67) = .63$  [.6400]

is due to the fact that collapsing bubbles, while consistent with Diba and Grossman's theoretical restrictions, introduce a degree of 'pseudo-stationarity' in the first difference of stock prices containing such bubbles. This spurious stationarity, which is brought about by the recurring collapses, causes a rejection of the unit root hypothesis for  $\Delta P_t$ , despite the presence of an explosive root in the conditional expectation of the bubble process. To show this point, Evans assumes a series for dividends which is stationary in first differences, i.e. is generated by a random walk with drift (as in (1.14), with  $\rho=1$ ), and constructs the associated fundamental price  $P_t^F$  as in (1.16), with the drift parameter  $\mu=0.0373$  and the white noise variance  $\sigma^2=0.1574$ .<sup>11</sup> The constant discount rate is set equal to 0.05. Collapsing bubbles are then constructed as in (3.37), with  $b=1$ ,  $p=0.85$  and  $\delta=B_1^*=0.5$ . The multiplicative disturbance  $\zeta_t$  is chosen to be IID lognormal with unit mean, i.e.  $\zeta_t=\exp(\xi_t-\tau^2/2)$ , where  $\xi_t$  is IID normal  $N(0,\tau^2)$ , with  $\tau=0.05$ . Bubbles so generated are then scaled up by a factor of 20, so that the sample variance of  $\Delta B_t^*$  is about three times that of  $\Delta P_t^F$ . This ensures that the bubble component provides most of the volatility in  $P_t=P_t^F+B_t^*$ . Based on these hypotheses, Evans computes 200 replications of the price series, each of 100 observations, and shows that Dickey-Fuller tests would in most cases reject the null hypothesis of a unit root in  $\Delta P_t$

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11. These values are obtained by fitting (1.14) to Standard and Poor's annual data over the period 1871-1980.

and detect cointegration between prices and dividends, thus failing to uncover the presence of sizable rational bubbles in the price process.

Evans' simulations weaken the conclusions drawn in Diba and Grossman's empirical work. Notice, however, that Dickey-Fuller test results on simulated prices including collapsing bubbles should be interpreted with extra care. In particular, since repeated and sudden bubble collapses are likely to introduce a considerable degree of heteroscedasticity in the resulting price series, a heteroscedasticity-consistent covariance matrix should be used to calculate the test statistics. In fact, the correction could be large enough to reverse the test response. In order to check this hypothesis, we run Dickey-Fuller tests as in Tables 4.3 and 4.4 on a sample of simulated prices with collapsing bubbles, assuming different values for  $p$  (one minus the probability of collapse), and  $b$  (the threshold level). Results show that rejections of the unit root hypothesis for  $\Delta P_t$  is actually much less frequent when H.C.S.E. are used.<sup>12</sup>

Finally, notice that, in principle, collapsing bubbles might be used to reconcile the EMT with the empirical evidence on price mean reversion and the associated dividend yield effect, under the assumption that mean reversion is simply due to repeated collapses. To investigate this hypothesis, we used the same sample of simulated

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12. The sample of prices with collapsing bubbles was kindly supplied by George Evans.

prices and the associated dividend series to construct corresponding series for returns and dividend yields. Results showed that the simulated dividend yield is not a good predictor of the simulated returns. Again, estimates are plagued with a considerable degree of heteroscedasticity.

We conclude this chapter with an indication that attempts to extend the FVM whilst keeping it within the fundamental rationality principles of the EMT have not been particularly encouraging. The time has now come for us to focus the analysis on those fundamental principles. We shall do so with the purpose of demonstrating that the limitations of the EMT are to be ascribed to such principles and are, as such, more congenital and elementary than what current research assumes them to be. Chapter 5 explains the rationale for our thesis, while Chapter 6 will provide some empirical evidence in its favour.

## CHAPTER 5

### CONVENTIONS AND THE STOCK MARKET GAME

#### I. Casinos and Stock Markets.

The "Mysterie and Company of the Merchants Adventurers for the Discoverie of Regions, Dominions, Islands and Places Unknowen", founded in London in 1553, is the earliest recorded example of Joint-Stock Company to appear in the economic history of Europe. This was the first company to replace the traditional practice of private fund raising with a public issue of paper certificates, incorporating the right for the holders to share in the profits and losses of the Company's ventures. The new instrument had the important advantage of spreading the risks of new enterprises - which were previously carried by the Company's partners alone - onto a wider group of private investors with different preferences, wealth and attitudes towards risk. Joint-Stock Companies became immediately very popular in England and throughout Europe, where a rapidly increasing number of people started buying share certificates in various enterprises.

It was not long after they began trading shares, thereby giving birth to stock markets. At the same time, a series of countless attempts to explain the behaviour of stock prices began.<sup>1</sup>

As shares represented claims to a company's future profits and losses, such explanations were not, in principle, particularly arduous to obtain: the price at which shares were traded had to be the result of some sort of compromise between sellers' and buyers' expectations about those profits and losses, discounted at a rate which reflected both time preference and investors' evaluation of the riskiness of the overall enterprise. In modern terminology, we say that the price was an estimate of the fundamental value of the issuing company, as represented by the discounted sum of its future uncertain stream of earnings, with the discount rate including a possibly variable risk premium.

Viewed on this background, the central claim of the EMT is that nothing essential has changed from the early days in which stock markets first appeared. Now as before, stock prices reflect the fundamental value of firms. The only major difference is in the dramatic improvement in investors' ability to forecast the prospects of future enterprises, which makes it plausible enough to assume that investors form rational expectations on those prospects - whence the FVM.

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1. For an interesting historical account of the origins of stock markets see Victor Morgan and Thomas (1969).

In Chapter 1 we contrasted the EMT to the Casino Market Theory (CMT). Unlike the EMT, the CMT regards stock markets as unreliable and potentially dangerous institutions, where investors' main activity is trying to outguess each other rather than estimating fundamental values, and stock prices reflect all sorts of perceptions and are only remotely related to firms' values. Keynes (1936, Ch. 12) is well-known to have equated stock markets to casinos, whereby he most likely intended to suggest that stock market investment is more akin to an unpredictable and risky game than to a virtuous capital allocating mechanism. It must be noticed, however, that Keynes' portrayal of stock market games has hardly any resemblance with casino games. As it turns out, in fact, the EMT implies a much closer resemblance between stock markets and casinos. Indeed, the very word 'martingale', which, as we have seen, plays such a fundamental role in the EMT, derives from a particular strategy which can be adopted by casino players.

Imagine a gambler playing a simple game of chance, say *rouge et noire* at the roulette (he is quite fed up with tossing coins). At time 1, he takes one pound from his personal wealth  $A_1$  and bets it on *rouge*. If *rouge* occurs, he wins one pound, otherwise he loses his bet. Imagine he plays the following strategy: If *noire* occurs at time 1, he wagers two pounds on *rouge* at time 2. If *rouge* occurs, he recovers his previous loss and wins one pound. If *noire* occurs, he bets four pounds on *rouge* at time 3, and so on. In general, if *noire*

occurs in the first  $t$  plays, he wagers  $2^t$  pounds on rouge at time  $t+1$ . The strategy of doubling the stake at each play until a win occurs is called a martingale, and is indeed a very rational strategy. Call  $T$  the random variable representing the first time rouge occurs:  $T$  has probability mass function  $P(T=t)=(1/2)^t$ , hence  $P(T<\infty)=1$  i.e. the player is almost surely guaranteed to win his pound in the long run. This is precisely why casinos do not allow gamblers to play the martingale strategy, or at least reserve croupiers the right to refuse the bets of gamblers who choose to play it.

Let  $E_t A_{t+1} = E(A_{t+1} | A_t, \dots, A_1)$  be the mathematical expectation of the player's personal wealth at time  $t+1$ , conditional on the 'history' of his wealth up to time  $t$ . Assuming for simplicity that rouge and noire are the only two possible events of the game, the latter is said to be 'fair' if the probability of rouge is the same as the probability of noire.<sup>2</sup> In this case, it is as if Nature determines  $A_{t+1}$  by adding a random shock  $\epsilon_{t+1}$  to  $A_t$ , with  $E_t \epsilon_{t+1} = 0$ . Hence  $E_t A_{t+1} = A_t$ , and we say that the stochastic process  $\{A_t\}$  is a martingale. It follows that a player who has rational expectations will expect his wealth to be unchanged at  $t+1$ , i.e. rational expectations on a martingale coincide with static expectations. In other words, if we define  $r_t = (A_{t+1}/A_t) - 1$  as the player's return from each play, we can say that the expected return from each play is

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2. We are of course disregarding the presence of a zero on the roulette wheel. Since croupiers win all bets if a zero occurs, the roulette is not really a fair game. Indeed it could not be, otherwise casinos would not play it.

equal to zero. Notice that such expectation is rational simply because it reflects the rules of the game, i.e. the true process generating  $A_{t+1}$ . In forming expectations about  $A_{t+1}$ , each player uses information available at  $t$ . In a fair game, the only relevant piece of information to be used to predict  $A_{t+1}$  is  $A_t$  and rational players, who know the rules of the game, will all agree on the fact that  $E_t A_{t+1} = A_t$ . This must be interpreted as: given  $A_t$ , it follows from the rules of the game that  $E_t A_{t+1} = A_t$ , hence  $E_t r_t = 0$ .

The Rational Expectations assumption is in this case an uncontroversial way to portray players' rationality. Since the process generating the outcomes (the rules of the game) is easy to understand and, more importantly, it is not affected by players' expectations, rational players can easily adapt their subjective expectations to the objective expectation of the true process. It is for this reason that we can base our theory of the behaviour of a rational casino player on the Rational Expectations assumption. Notice, for instance, that only on the basis of the Rational Expectations assumption can we argue that casino gamblers are either risk-neutral or risk-loving individuals, but cannot be risk-averse. A risk-averse individual would play a casino game only if he did not know or understand the rules.<sup>3</sup>

Now let the player be an investor, and the casino be the stock market. A stock market can be viewed as a special kind of casino

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3. As it is probably true, at least in some cases.

where investors can enter or exit at the beginning of each period  $t$  by exchanging part of their personal wealth for a corresponding amount of shares with unit price  $P_t$ . Assume there are no transaction costs and that there is a continuum of shareholders  $i \in [0,1]$  in the space of expectations, distributed on the unit circle.  $P_t$  is the share price quoted at the beginning of time  $t$ . For each share he owns, a shareholder is entitled to an uncertain stream of profit quotas (dividends)  $D_t$ , which he receives at the beginning of each period, starting from  $t+1$ , until he decides to sell the share. When he does so, say at  $t+N$ , he has the right to convert his share into cash at price  $P_{t+N}$ . For instance, if he holds the share for only one period, his return will be given by equation (1.1). In this stylised stock market place,  $P_t$  is determined by a market-maker in the process of regulating the demand and supply of shares at each  $t$ . The market-maker's job is to impose a simple market-clearing rule: For every player who wants to cash his share (a seller), he has to find another player willing to provide the cash, thus becoming the new holder of the share (a buyer).

As we can see, our stock market is, in principle, a singularly unexciting kind of casino, where the only game to play is one in which players are paid random bonuses just to be there. In fact, a shareholder's return comes only from collecting dividends, until he decides to sell his share, at which time he also realises a capital gain or loss. This game is called 'Buy-And-Hold' (BAH), and, unlike

casino games, can be played even by risk-averse players, provided that expected dividends are sufficiently high and not too risky. BAH is indeed the game stock markets were originally intended for and, as we have seen, were it the only game shareholders could possibly play, understanding stock price movements would be a much easier task than it actually is. Expected dividends and discount rates would be the only elements required to explain current price levels, and share transactions would arise for two reasons only. First, buyers and sellers may have different expectations about future dividends and/or different discount rates, which in turn may reflect different time preferences, evaluations of and attitudes towards risk. In this case they will attach different values to the same share - where by definition values are the discounted sums of expected dividends. An investor  $i$  who attaches a value  $P_{it}$  to the share will be willing to sell it to another investor who is prepared to pay for it  $P_{it}$  or more, or to buy it from an investor who is willing to sell it for  $P_{it}$  or less. The actual transaction price  $P_t$  will then be somewhere in between the bid and the ask price, as established by the market-maker, and the investor's expected profit from the transaction will be equal to  $P_{it} - P_t$ . Secondly, trades may occur between investors who, though sharing the same views about fundamental values, are willing to trade for reasons other than profit. For instance, a firm might want to sell a participation in another firm in order to finance investment in some other business. In this case it will try to

establish, in accordance with the buyer, a 'fair' price for the shares and the trade will occur at the agreed price, with none of the two parties expecting to make a profit at the expense of the other.

In both cases the resulting price  $P_t$  will be the best estimate of the fundamental value of the share - precisely as argued by the EMT. Hence an alternative way to express the EMT is to say that BAH is the only possible game to be played in stock markets and that all other games are impossible, i.e. not worth playing by rational investors. In particular, the EMT entails the impossibility of what we can call the Speculation game.

Let  $F_{it}(P_{t+1}+D_{t+1})$  be player  $i$ 's current subjective expectation on his wealth at  $t+1$ .  $F_{it}$  is the subjective expectation operator. Let  $\rho_{it}$  be  $i$ 's subjective discount rate which, for risk-averse players, includes a risk premium related to the perceived riskiness of shareholding over period  $t$ , relative to a risk-free investment. Define:

$$P_{it} = (1+\rho_{it})^{-1}F_{it}(P_{t+1}+D_{t+1}) \quad (5.1)$$

Then the Speculation game is the following. If  $P_{it}$  is greater than  $P_t$ , player  $i$  buys at  $t$  and sells at  $t+1$ ; If  $P_{it}$  is lower than  $P_t$ , he sells at  $t$  and buys at  $t+1$ . In both cases he will realise, in addition to the dividend yield  $D_{t+1}/P_t$  (the realised one-period return from playing BAH), a capital gain (if his forecast turns out

to be right) or a capital loss (if his forecast is wrong), equal to the percentage change in the share price between  $t$  and  $t+1$ .<sup>4</sup> Since by definition  $1+\rho_{it}=F_{it}(P_{t+1}+D_{t+1})/P_{it}$  and  $1+F_{it}r_t=F_{it}(P_{t+1}+D_{t+1})/P_t$ , player  $i$ 's expected one-period return  $F_{it}r_t$  will in both cases be higher than his discount rate  $\rho_{it}$ , whereas  $F_{it}r_t=\rho_{it}$  if  $P_{it}=P_t$  for all  $i$ .

$P_{it}$  can be seen as the limit price at which speculative player  $i$  plans to buy (sell) at time  $t$ , with the intention of selling (buying) at time  $t+1$ . Buyers will buy at less than  $P_{it}$ , sellers will sell at more than  $P_{it}$ , but if  $P_{it}=P_t$  neither will play. Assume that limit prices have a frequency distribution  $f(P_{it})$  across players and define  $N_s$ =number of sellers,  $N_b$ =number of buyers,  $N_h$ =number of holders. With many players distributed on the unit circle and no transaction costs, the frequency distribution  $f(P_{it})$  can be approximated by a continuous density function, with  $N_h=0$ .

*Ex ante* (before trade takes place at the beginning of time  $t$ ),  $N_s$  may or may not be equal to  $N_b$ . If not, the market-maker will set  $P_t$  so that  $N_s=N_b$ . If, at a given  $P_t$ ,  $N_b$  is bigger (smaller) than  $N_s$ , he will bid the price up (down) to the point at which  $N_s=N_b$ . Hence

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4. Of course, the dividend yield can only be realised either by the buyer, if the share is sold before the ex-dividend date, or by the seller, if it is sold after that date, but not by both. Also,  $D_{t+1}/P_t$  is the realised one-period return from BAH. It may be argued that the one-period return from BAH should include the accrued capital gain or loss, although the latter could only be realised by selling the share. However, by definition, players who play Speculation are only interested in realised returns, hence their decision to play will depend on whether the expected realised return is higher than the realised dividend yield.

the market-maker's job is to find the median of  $f(P_{it})$ , since by definition such is the value of  $P_{it}$  at which  $N_s=N_b=1/2$ . Thus:

$$P_t = \text{med } f(P_{it}) \quad (5.2)$$

## II. Stock Market Games.

By allowing  $P_{it}$  to differ across players, we have implicitly allowed players to form heterogeneous expectations. Common practice in Economics requires that heterogeneous expectations should be related to heterogeneous information, thus treating beliefs as probabilistic knowledge. In the language of the EMT, for instance,  $P_{it} \neq P_t$  means that, on the basis of his subjective discount rate and the information set available to him at time  $t$ , player  $i$  knows (in probabilistic terms) that by playing Speculation he will earn a one-period return higher than his one-period discount rate. It follows that, as long as players are identically rational, have the same discount rates and share the same information set,  $P_{it}$  is bound to be identical across  $i$ , say equal to  $P_t^H$ .<sup>5</sup> In this case,  $f(P_{it})$  degenerates at  $P_t^H$  and (5.2) becomes:

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5. Notice that, in principle, the existence of a spectrum of  $P_{it}$  across players may be simply due to differences in discount rates (to be explained along the lines of the CCAPM examined in Chapter 3), with players sharing the same expectations about  $(P_{t+1}+D_{t+1})$ . It should become clear in the sequel, however, that expectational differences are to be regarded as the crucial factor to account for differences across  $P_{it}$ .

$$P_t = P_t^H = (1+\rho_t)^{-1}F_t(P_{t+1}+D_{t+1}) \quad (5.3)$$

Trivially,  $P_t$  is still the median of  $f(P_{it})$ , but if  $P_t^H > P_t$  all speculative players will be buyers, while if  $P_t^H < P_t$  they will all be sellers. Hence the only equilibrium in the Speculation game will be at  $P_t = P_t^H$ , where  $\rho_t = F_t r_t$  (this follows from (5.3) by definition). At this point, the market-maker announces  $P_t$ , but speculative players do not play. Thus we conclude that the Speculation game is impossible among identical players with homogeneous information.

It is clear, however, that this result does not depend on players' expectations being rational, since it is the equality rather than the rationality of expectations which, together with identical discount rates, makes Speculation impossible. The game would be impossible even between identically irrational players. In this respect, notice that the EMT is just a special case of (5.3) in which the homogeneous subjective expectation operator  $F_t$  coincides with the objective mathematical expectation operator  $E_t$ , i.e. players have rational expectations and we write:

$$P_t = P_t^H = (1+\rho_t)^{-1}E_t(P_{t+1}+D_{t+1}) \quad (5.4)$$

which, since  $\rho_t = E_t r_t$  by definition, coincides with equation (1.3). The Rational Expectations assumption is however quite distinct from

the assumption of homogeneity, which is ultimately responsible for the impossibility of Speculation.

With homogeneous expectations, the only possible game to play on the stock market is BAH where, as we already noticed, transactions can only occur for non speculative purposes. Heterogeneous expectations are however only a necessary but not a sufficient condition for Speculation to take place. If, despite having different expectations, shareholders play only BAH, and believe that all other players do the same, then their decisions to buy and sell shares will depend entirely on their discount rates and their expectations about future dividend streams. In this case, as we have seen, the market-maker will clear the market if he finds a price which represents a suitable agreement between buyers and sellers about the value of prospective dividends, discounted at a rate which may include a (possibly non constant) risk premium. Hence the price itself will only depend on discount rates and dividend expectations and, under Rational Expectations, it will be the discounted sum of rationally expected dividends. If, moreover, each player believes that most other players play BAH, then he knows that in order to forecast prices he has to forecast other players' discount rates and expected dividends, since only discount rates and dividend forecasts affect prices. But, just like personal wealth in casino games, discount rates and dividends streams are independent of individual players' expectations. It follows that a learning process can take place,

whereby players learn how to form rational expectations of future discount rates and dividends. This explains our earlier claim that the EMT bears a closer resemblance to a casino game than the CMT itself. Only under Rational Expectations, in fact, will the process generating stock prices be ultimately independent of players' expectations.  $E_t D_{t+1}$  - the rational expectation of  $D_{t+1}$  - will simply reflect the process generating  $D_{t+1}$  up to a random error, and  $E_t P_{t+1}$  - the rational expectation of  $P_{t+1}$  - will likewise reflect the process generating  $P_{t+1}$ . This is given by (5.4), shifted one period ahead, hence it depends on  $\rho_{t+1}$ ,  $E_{t+1} D_{t+2}$  and  $E_{t+1} P_{t+2}$ . Of these, the first two will be determined at  $t+1$  in the same way as  $\rho_t$  and  $E_t D_{t+1}$  were determined at  $t$ , while the third will be given by (5.4), shifted two periods ahead. As this process is carried forward, the result is the FVM (provided the transversality condition holds), whereby  $P_t$  emerges as the discounted sum of rationally expected dividends and, just like  $\{A_t\}$  in casino games, the process  $\{P_t\}$  is ultimately independent of players' expectations. Moreover, as in casino games, only information at  $t$  (as represented by  $P_t$  and  $\rho_t$ ) is relevant in predicting  $(P_{t+1} + D_{t+1})$ , while information prior to  $t$  is worthless. Thus, if all players play BAH (and this is common knowledge among them), the stock market is informationally efficient. Stock prices move only according to fundamental information and possess the Markov property: conditional on the present, the future does not depend on the past.

In order to allow for Speculation, heterogeneous expectations must then be complemented with a disposition on the part of speculative players to profit not only from the collection of dividends (as in BAH) but also (and we might add mainly) from the realisation of capital gains, to be earned through recurrent moves in and out of the market. Since the existence of such an attitude among stock market players is a fact which can hardly be disputed, we can dismiss the hypothesis that BAH is the only game played by stock market investors. However, since the intention to play a different game does not prove *per se* that the game is possible, the actual existence of Speculation depends critically on the assumption of heterogeneous expectations, on which we shall now focus our analysis.

Economists are used to regard rationality as a fundamental axiom of economic modelling. In this respect, the Rational Expectations Hypothesis is just a natural extension of the rationality axiom to the analysis of information processing. But unlike some other fundamental tools of economic analysis (like preferences, endowments or risk aversion), the concept of rationality - however defined - does not lend itself to be easily differentiated across economic agents. In fact, it is quite natural to regard rational agents as identically rational, in the sense that, when faced with the same problem under the same conditions, they would produce the same response. Expectational rationality is no exception,

and for this reason the Rational Expectations assumption is usually employed in a representative agent framework.

Economists have strong arguments in favour of the rationality axiom, and most of these apply as well to the alternative between rational and non rational expectations. The usual story has it that arbitrary subjective expectations will converge towards the objective expectation of the true process of reality as agents learn how to avoid systematic expectational mistakes. As already remarked, this process of convergence to rational expectations is quite straightforward in the case of casino games, where the process generating successive values of personal wealth  $A_t$  is easy to understand and, more importantly, the outcome of the game is independent of players' expectations. This makes fully acceptable the notion that rational casino players can avoid systematic mistakes through a trial-and-error process, thereby learning that their wealth follows a martingale process.

The case for stock market players is however considerably different. Although at first glance equation (5.4) may look very similar to the martingale property of casino games (as it is customarily noticed by EMT theorists), there is in fact a substantial difference between the two. As we know, the martingale property of fair casino games reads: Given  $A_t$ , then  $E_t A_{t+1} = A_t$ . Equation (5.4), on the contrary, reads: Given  $P_t^H = (1 + \rho_t)^{-1} E_t (P_{t+1} + D_{t+1})$ , then  $P_t = P_t^H$ . Here, unlike fair casino games,  $E_t (P_{t+1} + D_{t+1})$  need not be the

objective conditional expectation of the true process generating  $(P_{t+1}+D_{t+1})$  for the equation to hold. In fact (5.4) is only a special case of (5.3), which is in turn a special case of (5.2). The latter represents the equilibrium condition for  $P_t$  and shows that  $P_t$  depends entirely on the distribution of  $P_{it}$  across players. The equation holds in general, independently of any specific assumption about  $P_{it}$ , and its special case (5.3) indicates that, given a common  $\rho_t$ , the market-maker determines  $P_t$  in such a way that the equation holds, *whatever* the common expectation about  $(P_{t+1}+D_{t+1})$ . Since in this way the market-maker rules out Speculation, the stock market can be said to be a fair game, but such fairness property is profoundly different from the fairness property of casino games. In the latter, fairness means that, independently of players' subjective expectations, their personal wealth follows a martingale, i.e.  $E_t A_{t+1}$  depends on (is equal to)  $A_t$ . Moreover, since rational players will learn to conform their subjective expectations to the objective martingale process for  $A_t$ , their expectations will be identically rational and the common rational expectation about  $A_{t+1}$  will be equal to  $A_t$ . In stock markets, on the other hand, fairness means that, *if* players share the same estimate of  $P_t^H$ , then the market-maker chooses  $P_t$  to equal this estimate, thereby making Speculation impossible. Hence in this case  $P_t$  depends on  $P_t^H$ , and not vice versa, and even though the process determining  $P_t$  may be easy to understand (in our stylised model it is given by equation (5.2)), it does inherently depend on players'

subjective expectations. The market-maker's choice of  $P_t$  simply reflects such expectations which, along with subjective discount rates, determine players' decisions to buy or sell shares at each  $t$ .  $P_t$  is just the median of the different  $P_{it}$ , and it is equal to  $P_t^H$  if  $P_{it}=P_t^H$  for all  $i$ .

Since the stock market game is not conceived as a fair casino game (as if  $(P_{t+1}+D_{t+1})$  were chosen by Nature by adding a random shock to  $(1+\rho_t)P_t$ ), it follows that, unlike fair casino games, a difference between  $P_{it}$  and  $P_t$  is not inherently inconsistent with the game. An inconsistency emerges only if  $P_{it}$  is the same for all players. In this case, as we have seen, the only equilibrium point is at  $P_{it}=P_t^H=P_t$ , where no speculative trade occurs because no player can expect his one-period return to differ from the subjective discount rate, and Speculation becomes impossible because it is self-defeating: if one player can do it, then all others can, hence no one can.

Follow this well-known example, which is often utilised by EMT theorists to corroborate the efficiency view. Imagine that someone spots a banknote on the sidewalk. Clearly, he will expect  $A_{t+1}$  to be greater than  $A_t$ . Fair casino games are such that, by definition of the rules of the game based on the laws of probability, there are no free banknotes on the sidewalk. Since all rational players can understand this, their subjective expectations will coincide with the unique objective expectation of the game, thus becoming a rational

expectations. In stock markets, on the contrary, no intrinsic rule of the game prevents the existence of a difference between the objective conditional expectation of  $(P_{t+1} + D_{t+1})$  and  $(1 + \rho_t)P_t$ , i.e. a free banknote on the sidewalk. However, if all players share the same expectation, then the banknote disappears or, more accurately, if a player spots one, then it must be false, otherwise some other player would have already picked it up.

This line of argument, which ought to be dubbed 'the Loser's Bias of Arbitrage Economics', relies on a quite misleading equivalence between a profit opportunity in stock markets and a banknote on the sidewalk. It is clear, in fact, that a profit opportunity and a banknote are very different objects indeed. This is true on two main counts. First, in stock markets, profit opportunities are usually 'hidden', i.e. they are not as immediately recognisable as a banknote on the sidewalk.<sup>6</sup> In this respect, the usual EMT argument is that rational stock market players will eventually learn how to find such opportunities, thereby eliminating them. There is indeed a large literature on learning in models with Rational Expectations where outcomes depend on expectations.<sup>7</sup> As

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6. We should point out that, while this is true for stock markets as a whole, 'visible' profit opportunities, involving virtually riskless arbitrage between assets which are perfect substitutes in terms of payoffs, do exist in financial markets as, for instance, in futures and options, or even for individual stocks within the market. However, the market as a whole has no perfect substitute, hence arbitrage cannot be riskless, i.e. profit opportunities must be hidden.

7. See, inter alia, De Canio (1979), Blume, Bray and Easley (1982), Jordan and Radner (1982), Bray (1985), Evans (1985, 1989a), Pesaran (1987, Ch.3) and the papers collected in Frydman and Phelps (1983).

noted by Radner (1983), however, virtually all these models are arranged in a homogeneous information framework, while "given the pervasiveness and importance of heterogeneous information in our economy, the theory of REE will have to come to grips with this phenomenon if it is to be an important part of economic analysis. But perhaps this is expecting too much" (p.137). Recall that, in accordance with our predilection for the naturally homogeneous concept of rationality, we are used to treat expectations as probabilistic knowledge. This means that we are prepared to justify heterogeneous expectations only on the grounds of differences in information. Only heterogeneous information - so the argument runs - can explain why identically rational individuals may form different expectations regarding the same reality. Therefore, if our goal is to justify the possibility of Speculation, we should concentrate on models in which Speculation occurs among differently informed players. But even this line of argument has its own problems. As shown by Aumann (1976), in fact, under Common Knowledge and identical priors, identically rational (Bayesian) individuals will not be able to maintain different beliefs, even if subject to heterogeneous information. Not surprisingly, following Aumann's argument, Milgrom and Stockey (1982) prove that, in such circumstances, the Speculation game remains impossible. In the same vein, Grossman (1976) and Grossman and Stiglitz (1976,1980) show that, if different beliefs

depend on heterogeneous (and costly) information, prices will reveal all available information, thus again making Speculation an impossible game to play.<sup>8</sup> Hence we must conclude that heterogeneous information *per se* cannot account for the possibility of Speculation, and that the hidden character of stock market profit opportunities is not sufficient to significantly differentiate them from banknotes on the sidewalk.

There is however a second and more fundamental difference between the two. Unlike banknotes, profit opportunities, even when apparent, are like the gods of Greek mythology: they appear in different shapes to different people. In more mundane terms, casual observation suggests that the notion according to which different expectations can only be sustained on the basis of heterogeneous information is difficult to reconcile with the fact that, even when faced with the same information, stock market players do not generally share the same views about the future value of stock prices, this often being, indeed, the immediate cause of their trades. The idea that information means different things to different individuals may be alien to the analytical framework of the EMT, but is nonetheless a rather obvious remark and a critical point to acknowledge in order to enhance our understanding of stock market behaviour. Most financial economists keep an ambiguous attitude

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8. The fact that Grossman and Stiglitz solve their information paradox by assuming an uncertain supply of shares is not relevant to our argument. On the same problems, see also Tirole (1982).

towards those "assumptions that are not even approximately satisfied empirically - for example, that agents have common priors (LeRoy (1989, p. 1611)). Some of them may occasionally recognise that "The majority of trades appear to reflect belief on the part of each investor that he can outwit other investors, which is inconsistent with common knowledge of rationality" (*ibidem*). At the same time, however, they all appear extremely reluctant to seriously question such fundamental principles as the assumption of homogeneous rational investors. Ingersoll (1987) provides a typical example of such a position. After completing a standard demonstration of the EMT, he comments: "In fact, the entire 'common knowledge' assumption is 'hidden' in the presumption that investors have a common prior. If investors did not have a common prior, then their expectations conditional on the public information would not necessarily be the same. In other words, the public information would properly also be subscripted as  $\Phi_k$  - not because the information differs across investors, but because its interpretation does. In this case the proof breaks down [...] The [...] problem cannot be corrected" (p.81). However, such dramatic remark has no repercussion on the rest of the book. Apart from adding that "differences in priors must come from inherent differences in the investors" - a sentence which is intended to sound implausible and to justify the assumption of common priors, but in fact reinforces the arguments against it - the problem is never mentioned again, although virtually all the proofs and

demonstrations contained in the next four hundred pages are crucially dependent on the common priors assumption. Indeed, this assumption constitutes the foundation of the entire modern theory of finance, as it provides a necessary support to its primary tool, the Arbitrage argument. Yet, it is quite difficult to explain why such a common place observation - really not much more than the basic notion that people have different ideas - keeps being swept under the carpet, instead of being granted the attention it deserves.

Its justification is indeed quite simple, and can be easily found by looking at equation (5.2), which describes the price generating process. Even assuming that each player  $i$  knows (5.2) and receives homogeneous information, it is quite clear that he can neither observe all other players'  $P_{jt}$  nor has any grounds, in general, to believe that all  $P_{jt}$  are equal to his own  $P_{it}$ . Players believe, instead, that the market is populated by a host of disparate individuals, each holding different beliefs about the effect that available information will have on other players' beliefs, and hence on stock prices. In Bayesian terms, we can say that, even if information is Common Knowledge, players' priors (i.e. the 'models' they use to interpret available information) are clearly far from being identical, and farther from being Common Knowledge.

To further illustrate this fundamental point, we can take as an example the announcement of the US monthly trade figures - which in recent times has been an important piece of market-sensitive

information. Whilst such an announcement reaches all major players at about the same time, it is quite evident that players do disagree among each other about the effect that the figures will produce on stock prices, and that they trade on the basis of their different beliefs. The parallel with casino games will again help us understand the peculiarity of stock markets. Imagine that the US trade figures are announced in a casino at time  $t$ . Since players know that outcomes are determined by Nature and have nothing to do with either the trade figures or players' expectations about them, they have no reason to expect the announcement to produce any effect on the game. In stock markets, on the contrary, outcomes depend crucially on each player's belief about the effect that the announcement will have on all other players' beliefs. Excluding the factually irrelevant case in which players play only BAH, it follows that, if enough players believe that other players will react to the trade figures, then prices will indeed move accordingly, irrespective - and this is the crucial point - of the actual effect that the implied evolution of US foreign trade will produce on the fundamental value of firms. In fact, our choice of the US trade figures as an example to illustrate the difference between casino and stock market games is not arbitrary in that, unlike (say) the number of monthly sunspots, trade figures are likely to be somehow relevant to firms' fundamentals. The key point is, however, that their effect on stock prices will not simply be a reflection of their effect on fundamentals, since the *trait d'union*

between world events and price movements via investors' beliefs - which is neutralised in the EMT through the assumption of Rational Expectations - does play an essential role in the process of stock price determination. In particular, the existence of such a link implies that players' price forecasts are affected by anything they believe to have an influence on the price forecasts of other players. In this respect, the difference between 'fundamental' information (as the US trade figures can in some sense be defined) and non fundamental information (like sunspots or, closer to the point developed in the next chapter, past price and dividend data),<sup>9</sup> is inessential. The nature of the stock market game is such that, if enough players believe that something has an effect on stock prices, then indeed it does. The fact that, in practice, trade data move prices, whereas sunspots don't, means only that investors as a whole do not regard sunspots as influencing future prices. This state of affairs is however entirely conventional. A convention is here defined as a belief which owes its reproduction to its being shared by a sufficient number of players. In this sense, conventions may tacitly establish themselves among players, whereby the latter condition their price forecasts on information which is entirely unrelated to firms' fundamentals, or react to fundamental information in a way which differs substantially from the prediction of the EMT.

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9. Remember that in the EMT bygones are bygones. In this sense, although past prices and dividends are fundamental variables, they do not constitute fundamental information on the current value of firms.

Clearly, it is not our claim that stock prices do not react to fundamentals (it is indeed quite obvious that they do), but that such reaction is essentially different from the one implied by the EMT and, in particular, does not preclude the possible influence of non fundamental information on the process of price determination.<sup>10</sup> The critical feature of such a process - the dependence of outcomes on players' beliefs about other players' beliefs - justifies the assumption of heterogeneous beliefs as a primitive concept and accounts for the possibility of Speculation. By affecting each  $P_{it}$ , all sorts of information available at  $t$  can generate changes in the median of  $P_{it}$ , i.e. changes in  $P_t$ . As players evaluate the available information, the distribution of their limit prices shifts to the right or to the left, thus producing changes in  $P_t$ .

### III. Keynes, conventions, fads and noise.

The idea that stock prices are influenced by non fundamental information is of course not new. Keynes, in particular - in Chapter 12 of the General Theory - expressed the view that stock markets are driven by a whole variety of considerations which are virtually unrelated to market fundamentals. Unfortunately, his position has

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10. Following Niederhoffer (1971), Cutler, Poterba and Summers (1989) have recently shown that fundamental macroeconomic variables, political developments and world events can explain only a small fraction of the variation in stock prices. On a related point, Roll (1988) shows that only a third of the monthly variations in stock returns can be explained on the basis of identifiable economic forces.

been often misread as an endorsement of the notion that stock markets are inherently 'irrational' and therefore unsuitable to material analysis. From this point of view, - which is rather typical of the layman who tries to disguise his lack of knowledge behind a veil of clumsy skepticism - stock markets look like bizarre congregations of lunatics, each acting on the grounds of his own eccentric and unpredictable whims, which the normal chap, who is immune to such unreasonable frenzies, should not bother to explain. Keynes, of course, was not so simple-minded. He was himself an expert stock market player and knew perfectly well that investing in shares may indeed be a subtle and elusive game, but is by no means an irrational one. He knew that, as a rule, investors are purposeful and consequent individuals, who pursue the maximisation of the return from their investments using all available knowledge and information. Thus, while observing that "the price of shares ... reveal[s] ... the average expectation of those who deal on the Stock Exchange" (p.151), he remarked that "the existing market valuation, however arrived at, is uniquely correct in relation to our existing knowledge of the facts which will influence the yield of an investment, and that it will only change in proportion to changes in this knowledge" (p.152, Keynes' italics). This passage should dispel all suggested affinities between Keynes and the naive 'irrationality' view. Indeed, if anything, the remark sounds very much like a defense of the EMT, except that the correctness of market valuations is not grounded,

according to Keynes, on the calculation of the mathematical expectation of future events - whose viability he notoriously rejected - but on the existence of a tacit convention among investors, which " - though it does not, of course, work out so simply - lies in assuming that the existing state of affairs will continue indefinitely, except in so far as we have specific reasons to expect a change" (p.152). In other words, as long as the convention is maintained, investors can rely on current prices as representing correct valuations. However, since the convention is founded on shared beliefs rather than rational expectations of discounted dividends, it follows that "in point of fact, all sorts of considerations enter into the market valuation which are in no way relevant to the prospective yield" (p. 152). Hence the conventional valuation of the market is correct because it is an equilibrium under the current state of knowledge, not because it coincides with the fundamental valuation as defined in the FVM.

Our comparison between casinos and stock markets is to be seen along the lines of Keynes' view. Thus our BAH game essentially coincides with what Keynes called 'enterprise', "the activity of forecasting the prospective yield of assets over their whole life", while our Speculation game describes "the activity of forecasting the psychology of the market" (p.158). Keynes thought of stock prices as resulting from a conflict between enterprise and speculation, and stressed that "it is by no means always the case that speculation

predominates over enterprise" (p.158). At the same time, however, he produced several arguments to demonstrate that professional investors "are, in fact, largely concerned, not with making superior long-term forecasts of the probable yield of an investment over its whole life, but with foreseeing changes in the conventional basis of valuation a short time ahead of the general public" (p.154). This state of affairs "does not even require gulls amongst the public to feed the maws of the professional; - [the Speculation game] can be played by professionals amongst themselves" (p.155). This observation led Keynes to formulate his famous 'beauty contest' example, which provides an effective characterisation of professional investors' activity of "anticipating what average [more precisely, median] opinion expects the average [median] opinion to be" (p.156). As a result, the eventual predominance of enterprise over speculation can only be due to the circumstance that 'fundamental' information has - on average and in the long run - a larger weight on the conventional basis of valuation relative to non fundamental information. Such circumstance, however, is itself entirely conventional, i.e. it is due to a particular (albeit natural) configuration of consensus beliefs, not to an intrinsic property of stock markets. In this regard, Keynes observed that "As the organisation of investment markets improves, the risk of the predominance of speculation does, however, increase" (p.158), and went on to suggest that "the introduction of a substantial government transfer tax on all

transactions" or of legislation making "the purchase of an investment permanent and indissoluble" (p.160) would possibly serve the purpose of protecting enterprise against speculation, by discouraging or entirely inhibiting speculative moves, although, by making capital assets less liquid, would at the same time discourage new investment.

Keynes' precepts may nowadays appear both questionable and impractical. Nonetheless, his insightful analysis of the conventional nature of the process of stock price formation merits attentive consideration. It is therefore quite unfortunate that his lesson has been neglected for a long time in the mainstream finance literature, where it has been typically rejected by resorting to the Arbitrage argument. We have challenged such a crude dismissal in the previous section. Here we need to add that our point of view is quite close in spirit to that expressed in an increasing number of recent studies which - following the debate stirred by Shiller's original paper on 'excess' volatility - contain a more attentive investigation of possible alternatives to the FVM and its Rational Expectations extensions. Notably, Shiller (1984) has given rise to a series of papers focusing on what is referred to as the 'fads' hypothesis.<sup>11</sup> Central to this hypothesis is the idea that, like most other institutions and practices of modern society, stock market investment is influenced by social movements and attitudes. Such a remark has a clear Keynesian tone: waves of optimism and pessimism, the diffusion

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11. Most Shiller's papers are now collected in Shiller (1989b). See also Shiller (1990a,b).

of opinions and fashions, changes in valuation practices and outlooks can all be seen as part of the conventional structure of investors' beliefs. Also, as in Keynes, models based on the 'fads' hypothesis distinguish among different categories of investors within the market. The most common distinction is between two groups of investors: one, referred to as 'smart-money' or 'sophisticated' or 'rational' investors who, just like the EMT representative investor, are assumed to correctly process available information and form rational expectations of fundamentals; the other, variably referred to as 'ordinary' or 'naive' or 'noise' or 'irrational' investors, who have no reliable model to calculate the true value of stocks and therefore hold incorrect beliefs about fundamentals.

A typical example of this line of research, beside Shiller (1984),<sup>12</sup> is a recent paper by De Long, Shleifer, Summers and Waldmann (1990a). Their model includes sophisticated investors and noise traders. Agents within the two groups are identical, but the representative sophisticated investor has rational expectations, while the representative noise trader is assumed to misperceive the expected stock price by an independent and identically distributed normal random variable, whose mean is a measure of noise traders' average 'bullishness'. In this set-up the equilibrium stock price is a positive function of the average price misperception of noise

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12. See also Black (1986), who has popularised the term 'noise traders', first introduced by Kyle (1985).

traders. If noise traders are bullish on average, they will be inclined to bear a larger share of price risk relative to sophisticated investors, who will therefore require a lower expected return and bid up the stock price. This 'pressure' effect is coupled with a 'shift' effect due to variations in noise traders opinions, as measured by the deviation of the misperception variable from its average. This effect picks up the increase in price which occurs whenever noise traders are more bullish than average. Finally, the stock price depends on the variance of noise traders' price misperception. This is a measure of 'noise trader risk', i.e. the uncertainty surrounding noise traders' beliefs. Sophisticated investors who believe that stocks are mispriced are willing to take an offsetting position, which will however be limited by the risk that noise traders will drive the price further in the wrong direction. Such a limitation applies because sophisticated investors have finite horizons - an assumption which tries to mimic the fact that fund managers' performance is usually evaluated at rather short frequencies (typically every quarter). Noise trader risk restricts the possibility of arbitrage, thereby increasing the expected return from stocks and depressing the price. Also, by limiting the extent of arbitrage, the risk due to the presence of noise traders guarantees that the latter will not be driven out of the market. Indeed, if noise traders' misperception is positive and stocks are undervalued relative to fundamentals, the model implies that noise traders will

earn a higher expected return relative to sophisticated traders, as a reward for bearing a larger share of risk.

The introduction of a permanent contingent of noise traders in models where only a fraction of stock market players are endowed with rational expectations constitutes the latest alternative to the traditional EMT paradigm. The obvious appeal of the new models is that the additional risk created by noise traders provides a possible explanation for the 'excess' volatility of stock prices. Also, by assuming serial correlation in noise traders' misperceptions, it is possible to explain stock price mean reversion and the predictability of stock returns using fundamental measures of scale, like dividend yields. In addition, De Long et al. show in the same paper that noise traders risk can be used to explain the Mehra-Prescott paradox and the discount of closed-end mutual funds relative to their net asset value. Using a very similar model, De Long et al. (1989) examine the negative effects of noise trading on real investment and welfare, while De Long et al. (1990b) analyse investment strategies based on the anticipation of noise traders' misperceptions and show that this kind of speculative behaviour may in fact increase price instability. This case is also investigated in Shleifer and Vishny (1990), who show that the structure of transaction costs for long term arbitrage, involving per period fees, provides another reason for assuming sophisticated investors with finite horizons. In a similar model Cutler, Poterba and Summers (1990b) consider three types of

investors: rational traders, who hold rational expectations of future returns; fundamental traders, whose expected returns depend on the relationship between prices and perceived fundamentals (with the latter being a function of lagged true fundamentals); and feedback traders, who extrapolate expected returns from past returns. Perhaps unsurprisingly, in such a model returns present positive serial correlation over short horizons, prices are mean reverting and lagged fundamental proxies forecast future returns. The notion that the universe of stock market participants may include noise traders is also closely related to ideas borrowed from cognitive psychology (see Kahneman and Tversky (1982)). The basic concept there, based on experimental evidence, is that people are subject to a series of 'heuristic biases', or rules of thumb which produce a distortion of their judgements and predictions relative to what could be rationally extracted from the underlying evidence. The most relevant of these biases in the case of noise traders is perhaps the so-called 'representativeness heuristic', i.e. the overweight of recent information relative to the underlying distribution of events. De Bondt and Thaler (1985, 1987) use this framework to present some evidence about investors' overreaction to news, based on the performance of 'contrarian' investment strategies, involving the sale

of securities which have gone up in price and the purchase of those that have gone down.<sup>13</sup>

Noise traders models are clearly focused on the right issues. There is however a possible criticism in that, insofar as they maintain the fiction of the sophisticated investor with rational expectations, these models end up neglecting an important feature of the Keynesian paradigm, namely the idea that the conventional structure of investors' beliefs is common to all market participants, irrespective of their particular skills as investors. In fact, while it is quite obvious that investment skills differ widely across the spectrum of stock market participants - which after all runs from professional fund managers to occasional punters - it is also rather evident that the criteria guiding those participants in their investment decisions are, in broad terms, fairly similar. Professionals may conduct a rigorous evaluation of companies and markets, based on elaborate quantitative techniques and on the informed advice of experienced analysts, while amateurs may simply look at crude valuation measures, like price-earnings ratios, or even follow the trend and act on positive feedback. But the distinction between the two groups is only a matter of degree and not of substance. Indeed, an unprejudiced observation of the actual behaviour of stock market professionals would easily reveal that the

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13. Similar evidence on unexploited arbitrage opportunities can also be found in Shefrin and Statman (1985) and Lehmann (1990). Overreaction to news in the aggregate stock market is investigated in Campbell and Kyle (1988).

decisions of even the most sophisticated among them are much more down-to-earth than what they are assumed to be in models which retain the parable of the rational investor - this legendary individual who is supposed to know the true process generating stock prices. The rather more mundane reality is that, regardless of their skill levels, all market participants are engaged in guessing future prices as best as they can, but nobody knows the right way to do it, simply because there isn't one. That is why (to borrow a somewhat trite cliché) investment is more an art than a science. On the other hand, the prevailing tendency, common to the EMT as well as to the noise traders literature, is still to designate as irrational those investors who react to non fundamental information. But this really amounts to begging the question of rationality in that, if one is prepared to accept that, due to heterogeneous beliefs, stock prices may depend also on non fundamental information, then there can hardly be anything irrational in using such information to predict stock prices.<sup>14</sup> It is precisely for this reason that market practitioners (analysts, stockbrokers, fund managers and the like), who are often cited in the finance literature as generators and/or recipients of noise information, are surely not worse than economists at understanding how stock markets behave, and one may even be a little

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14. In a recent review of the noise traders literature, Shleifer and Summers (1990) admit that "It becomes hard to tell the noise traders from the arbitrageurs" (p.26). In the same vein, Cutler, Poterba and Summers (1989) acknowledge that "Throwing up one's hands and simply saying that there is a great deal of irrationality that gives rise to 'fads' is not constructive" (p.9).

audacious and venture to say that they are actually better, despite being a recurring target for economists' often unwarranted sarcasm. This is not not to say, of course, that the market place is only populated with wise individuals.<sup>15</sup> The point is rather that the ultimate cause of stock market inefficiency cannot be simply ascribed to irrationality, as it has much more to do with the intricate mechanisms of collective rationality, where the interaction of individually rational agents gives rise to aggregate outcomes which can in some sense be considered sub-optimal or irrational as a whole. A rigorous treatment of this problem in the context of financial markets constitutes a worthwhile - albeit arduous - endeavour for future research.

In the final part of this study we shall provide some empirical evidence in support of our thesis. As anticipated, the evidence will take the form of traditional orthogonality tests, where current stock returns are regressed against lagged information which can be expected to play a role in the configuration of investors' beliefs in the market. Such an empirical strategy coincides with that supporting noise traders models, except that we do not deem it necessary to associate different lagged responses to different investor types. Once it is agreed that investors in general try to predict stock

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15. Indeed, if one wanted truly tangible evidence of stock market inefficiency, all he should really do is to go out to lunch with a stockbroker. After this, he would comfortably feel in the position to entirely skip the next chapter. In other words, there are bad as well as good financial experts, but after all the same is true for economists.

prices rather than fundamental values, then the important task is to look for those variables which, being part of the conventional structure of beliefs, produce changes of the distribution of investors' limit prices.

## CHAPTER 6

### SOME EMPIRICAL EVIDENCE ON MARKET CONVENTIONS

#### I. Stock Market Conventions.

We examined in the previous chapter the fundamental difference between stock market games and fair casino games, with which the former are usually associated by EMT theorists. We have seen, in particular, that the nature of stock market games is consistent with the existence of heterogeneous beliefs about the value of future stock prices, and that such heterogeneity is not necessarily due to heterogeneous information, as different investors may interpret the same information in different ways (i.e. according to different priors or models). Heterogeneous beliefs about future prices allow for the possibility of speculation and justify the existence of tacit conventions, whereby stock market players rationally condition their price forecasts on information which is unrelated to market fundamentals, or on fundamental information in a way which is significantly different from the predictions of the EMT.

Watching a TOPIC screen<sup>1</sup> flashing continuously for eight hours a day makes arguing for the possibility of Speculation look like a rather odd and superfluous exercise. True - as EMT theorists would contend - the mere existence of speculative players is not sufficient to demonstrate the possibility of Speculation, in the same way as the existence of casino players will not prove that their personal wealth during the game does not follow a martingale. Indeed, tests of the EMT based on the historical performance of professional investors prove it very hard to demonstrate that fund managers are able to consistently beat the market over long time spans.<sup>2</sup> However, such tests can hardly constitute compelling evidence in favour of the EMT, since the difficulty of detecting outperformance over long periods of time may well be related, for example, to the personal history of successful professional investors - who may change company or get to manage bigger and less controllable funds - rather than to the actual impossibility of success. It is interesting to notice in this regard that the EMT, which is so crucially dependent on the rationality axiom, could not be reconciled with the very existence of the investment management industry, if not by allowing portfolio managers and their clients to be subject to an outright irrational illusion about the possibility of outperformance. In addition, it is clear that the mere difficulty of outperforming the market can only

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1. TOPIC is the London Stock Exchange on-screen information system.

2. Jensen (1968) is the traditional reference on this subject.

demonstrate the complexity of the return generating process, but cannot *per se* constitute evidence in favour of the EMT hypothesis, according to which excess returns follow innovation processes. Remember that if monkeys can't play Bach it does not necessarily follow that Bach cannot be played. It should be clear at this point that such a remark is not meant to sound contemptuous towards stock market players, although the comparison is admittedly a little too extreme in that, unlike monkeys playing Bach, some players may well be able to play the stock market game well enough to produce the rewarding sound of outperformance. Indeed, this is the prime reason why they play the game in the first place. Players believe that, contrary to the predictions of the EMT, it is possible to acquire and correctly interpret relevant information about future prices which has not been already incorporated into current prices. In the symbols adopted in the previous chapter, investors believe that  $P_{it} \neq P_t$ .

In this respect, casual observation suggests that information which is somehow related to the future profitability of firms has an overwhelming importance in the process of price forecasting. Investors tend to buy shares in companies which they expect to do well in the future and to sell companies on which they have a less favourable outlook. But although the predominance of fundamental information for the purpose of price forecasting would seem at first glance to fit in the main tenet of the EMT, the arguments presented in the previous chapter suggest that the reaction of stock prices to

fundamental information is part of the conventional nature of the stock market game, which allows stock prices to react to fundamental information in a way which differs from the predictions of the EMT and is consistent with the hypothesis that non fundamental information has an important influence on the process of price determination. Such an implication constitutes the basis for the empirical strategy followed in this final chapter: testing whether prices are influenced by non fundamental information will at the same time provide a test of the EMT. Indeed, we shall perform the same orthogonality tests which have countless times been employed by EMT theorists to corroborate the efficiency hypothesis. As we have seen in Chapter 2, the practice of interpreting the negative results of such tests as evidence in favour of the EMT is liable to several methodological and statistical drawbacks, which cast serious doubts on the alleged interpretation of the results. These same drawbacks would however turn into a powerful reinforcement of the evidence, should positive results be obtained. Performing orthogonality tests is in fact like asking the suspect whether he killed the victim: Although a denial should not be taken as evidence of his innocence, a confession may well be sufficient to convict him.<sup>3</sup>

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3. Provided, of course, that no form of torture is exercised. Torture in economics is called data mining. Indeed, the investment management literature is plagued with 'empirical regularities' obtained through sapient but meaningless manipulation of the data. To protect our results from the risk of data mining, three basic precautions have been adopted: first, we looked for sound theoretical underpinnings of the empirical relationships under analysis; second, we checked that the relationships are reasonably stable over time; third, we made sure that similar relationships held across different markets.

The most important kind of non fundamental information which we expect to have an influence on current returns consists of past information. We ought to distinguish at this point between fundamental variables - variables which we regard as somehow related to the fundamental value of firms - and fundamental information, which in the context of the EMT can only denote information about the *future* value of fundamental variables. Remember that, according to the EMT, past information - whether or not it regards fundamental variables - is already reflected into current prices and therefore, like any kind of non fundamental information, should have no effect on current returns.

The hypothesis that past information affects current returns raises an immediate objection. If such a relationship exists, it should be possible to devise a 'money machine' to predict future returns and generate consistent excess performance. At this point, what we called 'the Loser's Bias of Arbitrage Economics' steps in, and the question is raised about why, if a money machine is feasible, hasn't anybody already made one. Whereby the conclusion almost immediately follows that the money machine is indeed unfeasible and that markets are efficient. Rather obviously, however, such an argument neglects the fact that, due to the complexity of the stock market game, the creation of a money machine may well be a very difficult task, whilst at the same time not an impossible one. The possibility of a money machine coincides with the proposition that

excess returns are not innovation processes, i.e. they are not uncorrelated with all past information. But uncovering an exploitable relationship between current returns and past information is a different matter. In the sequel, some examples of such a relationship will be presented, which may be regarded as rudimentary versions of a money machine. But the question whether such machines are good enough to actually generate consistent outperformance will not be addressed in the present study.

Our search for significant effects of past variables on the return generating process starts from some general hypotheses about the process itself. Returns are defined as in (1.1), i.e.  $r_t = (P_{t+1} + D_{t+1})/P_t - 1$ , where  $P_t$  and  $D_t$  are the real price and dividend levels at the beginning of time  $t$  (which in our data set coincides with the end of each calendar month). Following standard practice, compound returns are calculated, for empirical purposes, as  $\ln(1+r_t) = \Delta \ln P_{t+1}^C$ , where  $P_{t+1}^C$  is a real cum-dividend price index at the beginning of  $t+1$ . Cum-dividend indices are computed on the assumption that accruing dividends are reinvested in the existing stock and provide a correct measure of the total return earned by investors. The logarithmic approximation improves normality of returns, while the use of month-end indices, rather than monthly averages, prevents the occurrence of spurious correlations among averaged data (see Working (1960)). Finally, notice that  $r_t$ , as we define it, is really a variable at  $t+1$ . Although it is customary in

the literature to define it as  $r_t$ , rather than  $r_{t+1}$ , we should not forget that other variables in  $t$  are lagged with respect to  $r_t$  and thus represent past information.

Our first hypothesis about the return process regards the combined effect on current returns of the lagged dividend yield and the lagged Average Gross Redemption Yield on Long Term Government Securities. These variables are indeed important determinants of professional investors' allocation decisions between different asset categories. The lagged dividend yield is regarded as an approximate measure of the appreciation potential of equity investment and should therefore have a positive effect on current returns, while the bond yield is taken as a measure of the opportunity cost of equity investment and should therefore have a negative effect. The difference between the two variables, known as the reverse yield gap,<sup>4</sup> is indeed a rather popular indicator of the underlying tendency of the stock market, and may be regarded as a proxy for what practitioners call the 'risk premium' - the difference between the dividend discount rate (the internal rate of return which equalises the discounted sum of future expected dividends to the current stock price) and the yield-to-maturity on a benchmark long bond instrument. The gap is however bound to be a poor proxy, since it does not include expected capital gains, which represent the unobservable

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4. The term 'reverse' refers to the fact that the difference, which used to be positive in the United Kingdom up to the 1950's, turned negative thereafter as investors (first, we are told, Scottish investors) began to realise the importance of capital gains.

component of risk premia. In addition, while bond yields are clearly affected by inflation, along the lines of the Fisher effect, dividend yields are more in the nature of real variables, as dividends and stock prices grow roughly in line with inflation. For these reasons, we begin our specification search with an unconstrained version of the gap, rather than one which requires the coefficients of  $DY_t$  and  $BY_t$  to have equal values and opposite signs. Notice also that, if yields are non stationary, we should expect them to appear in delta form when regressed on real returns, unless  $DY_t$  and  $BY_t$  are in fact cointegrated.

As seen in Chapter 4, the predictive power of dividend and bond yields on future returns is strictly related to stock price mean reversion and, as such, represents a serious challenge to the EMT. On the other hand, we have also seen that return predictability may still be consistent with the EMT, provided that expected returns are time-varying. In such a case, however, the lagged yield effect should disappear once the variability of expected returns is explicitly accounted for. One simple way to do this is to include among the regressors an approximate measure of return volatility, such as the 12-month moving standard deviation of past returns around the corresponding moving average, defined as:

$$(MSD12r)_{t-1} = \sqrt{\frac{\sum_{i=1}^{12} (r_{t-i} - (MA12r)_{t-1})^2}{12}} \quad (6.1)$$

If the investor population is risk-averse, the average reward received by risk takers must be higher than the average reward received by risk avoiders. Thus a positive coefficient on (6.1) should reflect the increase in the risk premium required by less risk-averse investors as compensation for bearing a higher level of risk. Likewise, if investors are risk takers on average, risk avoiders will receive a reward for staying out of the market. Hence in this case (6.1) should have a negative coefficient.<sup>5</sup> If, after including (6.1) among the regressors, the coefficients of the lagged dividend and bond yields are driven to zero, we should conclude that the yield effect is a mere proxy for risk and is therefore consistent with the EMT. If, on the other hand, the two yield measures are still significant, then we could argue that their effect is independent of time-varying risk, and that it may rather be a reflection of a conventional practice adopted by stock market players in the process of predicting future prices. However, since (6.1) is probably a poor proxy for return volatility, we shall allow ourselves to draw this conclusion only after controlling more adequately for time-varying

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5. A more appropriate method to directly account for return volatility is to model it as a GARCH process, as in Attanasio and Wadhwani (1989) and Attanasio (1989), since, from an investor point of view, the ex ante uncertainty about future returns matters more than their actual variability (as measured by (6.1) or, more simply, by lagged squared returns). A Monte Carlo experiment described in the first paper actually shows that, if past variability is used as a proxy for ex ante volatility, the OLS regression coefficient may be downward biased.

expected returns, within the framework of a production-based CAPM, as suggested by Balvers et al. (1990).

Our second hypothesis about the return process regards the effect of lagged inflation. In the past fifteen years, a large number of studies have investigated the possible effects of inflation and inflationary expectations on real activity and firms' profitability. In particular, several distortions brought about by inflation on the calculation of reported earnings (notably on depreciation charges, inventory levels, capital gains, interest payments and tax charges), have been pointed out as having a negative effect on profitability levels. Also, inflation has been associated with the possible existence of inflation illusion, which induces investors to discount real expected cash flows using nominal discount rates.<sup>6</sup> All these hypotheses refer, however, to a negative relationship between current returns and current or expected inflation, hence are not *per se* inconsistent with the EMT. On the other hand, a negative relationship between current returns and *lagged* inflation (after adjusting for varying risk) would be in contrast with the efficiency view while, at the same time, could be reconciled with the above hypotheses, in so far as there is a positive relation between actual inflation and inflationary expectations.

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6. See, *inter alia*, Nelson (1976), Fama and Schwert (1977), Modigliani and Cohn (1979), Feldstein (1980), Fama (1981), Gultekin (1983), Stulz (1986), Mullins and Wadhvani (1990).

Rather than simply using lagged inflation levels (as, for instance, in Pesaran (1989)), we prefer to account for a lagged inflation effect using a 12-month moving standard deviation of past year-on-year consumer price inflation rates, defined as:

$$(\text{MSD12INF})_t = \sqrt{\left[ \sum_{i=0}^{11} (\text{INF}_{t-i} - (\text{MA12INF})_t)^2 / 12 \right]} \quad (6.2)$$

where  $\text{INF}_t$  is the actual 12-month change in the log of the Consumer Price Index and  $(\text{MA12INF})_t$  is its 12-month moving average.<sup>7</sup> A negative coefficient on (6.2) should reflect the negative influence of volatile (rather than simply high) inflation rates on investors' estimates of fundamentals.

Our third hypothesis is that the return process retains a certain degree of inertia, which is not adequately captured by a simple lag polynomial of past returns.<sup>8</sup> Hence we calculate a 12-month moving average of past monthly returns, defined as:

$$(\text{MA12r})_{t-1} = \sum_{i=1}^{12} r_{t-i} / 12 \quad (6.3)$$

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7. Remember that (6.2) is lagged relative to  $r_t$  since by definition  $r_t$  is a variable at  $t+1$ .

8. The insignificance of lagged returns regressed on current returns is well-known to support 'weak' stock market efficiency.

Such a variable is used as an indicator of the momentum of the return process. A positive coefficient indicates that a positive (negative) trend of returns over the previous twelve months has a positive (negative) effect on current returns, as it induces more players to be buyers (sellers) in the current month. It also reflects the practice of 'Technical Analysis', that bizarre agglomeration of graphical and quasi-voodoo techniques which tries to predict the future course of stock prices using a weird mixture of moving averages and hand-waving 'psychological' nonsense. Technical Analysis epitomises as well as anything the conventional nature of the process of stock price determination, which compels otherwise dignified intellects to join the ranks of techno-loonies just because, as they correctly say, as long as the market believes them, "that's the way it works".

A second measure of price momentum is given by the lagged first difference in monthly returns,  $\Delta r_{t-1}$ . A positive coefficient on such a variable should reflect the improvement (deterioration) in 'market sentiment' which follows an acceleration (deceleration) of the price process in the previous month. Notice that, as real returns are stationary variables, both (6.1) and (6.3) (and obviously  $\Delta r_{t-1}$ ) should also be stationary, although the smoothing involved in their construction might well decrease the power of unit roots tests in rejecting non stationarity. The same is very likely to be true for (6.2) for identical reasons.

Our last conjecture about the behaviour of stock returns regards the influence exerted by the New York stock market on the performance of the other world markets. As Wall Street often sets the tone on the performance of the other markets, we would expect current local returns in each market to be negatively affected by the gap between local and New York market prices, as reflected by the log of the ratio between their respective real indices,<sup>9</sup> lagged one month,  $LOCUS_t = \ln(P_{LOC}/P_{US})_t$ . Like the moving average of returns and the delta return,  $LOCUS_t$  is a trend variable, in that it has no immediate relation with the fundamentals of the domestic country and is primarily an indicator of market sentiment relative to past trends in domestic and/or foreign stock prices. On the other hand, in accordance with our earlier definition, we shall refer to lagged dividend and bond yields and to return and inflation volatility as fundamental variables because, although they represent past information, they are directly related to market fundamentals.

A final word on timing: in the following equations, returns between the beginning of time  $t$  (31 December, say) and the beginning of time  $t+1$  (31 January) are regressed against a subset of information available at  $t$ , which includes past returns, up to  $r_{t-1}$

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9. Notice that taking the ratio between real indices is equivalent to correcting the ratio between nominal indices by the consumer price level ratio, which coincides with the simplest version of the Purchasing Power Parity exchange rate. Since exchange rate volatility might introduce excessive noise in the estimates, we choose to use a real price ratio rather than the corresponding nominal price ratio corrected for the actual exchange rate between the local currency and the dollar.

(the rate of return earned in December), the stock price level and the dividend and bond yields at time  $t$  (which can actually be observed at 31 December), plus the consumer price index at  $t$ . Notice that, in practice, this last variable is not observable until some time after  $t$ ,<sup>10</sup> hence, strictly speaking, it is not available at  $t$ . However, the high degree of autocorrelation present in consumer price series makes the approximation innocuous enough to be negligible. We use consumer price indices to deflate the nominal stock price index (and compute real returns) and to calculate annual inflation rates (and their moving standard deviation). As far as the first operation is concerned, notice that there is very little difference, on a monthly basis, between nominal and real returns.<sup>11</sup> As for the second, annual inflation rates cannot differ too much from inflation rates over the previous eleven months, which are actually available at  $t$ .

## II. Empirical Results.

On the basis of the above hypotheses, we performed a number of orthogonality tests on samples of monthly data relative to the UK, US, Japanese and Italian stock markets, spanning the period from 1970

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10. Monthly consumer price indices are usually published with a lag of two weeks to one and a half month.

11. In fact, using nominal rather than real returns in our equations yields very similar empirical results. Another way to eliminate the current price level is to use the excess return of stocks over a risk-free asset as the dependent variable. Again, results are quite similar.

to 1988.<sup>12</sup> Our principal aim was to test whether, as predicted by the EMT, the lagged variables presented in the previous section have zero coefficients when regressed on current monthly returns. The latter have been calculated using the Morgan Stanley Capital International (MSCI) Cum-Dividend Indices (Month-End), deflated by the Consumer Price Index. MSCI indices represent the standard benchmarks against which the performance of professional investors is currently evaluated.<sup>13</sup>

The first stage of our estimation strategy was to fit a common general model on all four markets, in order to observe common patterns in their return behaviour. This general model includes a constant and all the variables described in the previous section, except  $LOCUS_t$ , which would not have had a suitable correspondent in the US equation. The first two lags of each regressor were included in order to pick up possible delta effects. This general model is presented as equation (1) in Tables 6.1-6.4 for each market.<sup>14</sup>

Notice that, even at first glance, the equations do not exactly appear as the dreary land imagined by EMT theorists. In the UK

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12. For Japan and Italy, equations have been estimated from 1973, for lack of a suitable dividend yield series for the preceding months.

13. See Data Appendix for a complete list of data sources.

14. Along with the usual statistics, each equation in the tables reports Lagrange Multiplier tests for autocorrelated residuals and ARCH tests for Autoregressive Conditional Heteroscedasticity of the first, first to fourth and first to twelfth order, the White's Heteroscedasticity Test and the Jarque-Bera Normality Test. The autocorrelation and heteroscedasticity tests are reported in their F-form, and are followed by F-probability levels under the null hypothesis.

equation, for instance, it is difficult to ignore signs of a delta effect in the two volatility measures, while the first lag of the moving average of returns and of the bond yield and the second lag of the delta return are very close to being significant (although the delta return does not have the expected sign). In the US equation there is a clear delta effect in the bond yield, and it is certainly worth checking for a similar effect in the dividend yield. The Japan equation, on the other hand, is much more like the typical EMT landscape. Here no variable shows any sign of vitality, a clear proof - according to EMT advocates - of the efficiency of the Tokyo stock market. Lastly, the Italian equation presents a strong effect in the moving average and in the delta return, while the two volatility measures call for further investigation.

The standard EMT theorist would not answer this call. In fact, he would probably dismiss altogether the evidence contained in the four equations as too scanty and inadequate, possibly the result of data mining (or, more politely, of a sample selection bias). Alternatively, he would interpret the correlations as evidence of time-varying expected returns, to be suitably explained within an appropriate extension of the EMT. Since we do not share such strong priors, we began our search just where the EMT theorist would have ended it. From our point of view, the allegation of data mining must lose force if we can show that the estimated coefficients are reasonably constant over time and that the same variables, chosen on

the basis of reasonable economic assumptions, play a similar role in explaining stock returns across different countries. As for the alternative hypothesis of time-varying expected returns, we have seen in Chapter 4 that it is indeed possible to test whether lagged variables are merely proxying for risk, by including among the regressors other variables, such as lagged output (or industrial production), whose correlation with current stock returns is consistent with a general equilibrium version of the EMT.

#### United Kingdom

As we just noticed, the general model in the UK suggests the presence of a delta effect in the two volatility measures and, possibly, of a positive coefficient for the first lag of the moving average of returns, together with a negative coefficient for the second lag of the delta return and for the first lag of the bond yield. In such circumstances it is rather obvious for the econometrician to try and isolate the signals from such variables by dropping from the model other variables which appear to be insignificant - be it because they are not related to current returns or because they are dominated by the stronger signals. Hence we proceeded to remove from the model the second lag of the moving average of returns, of the dividend yield and of the bond yield, which are clearly dominated by their respective first lags, and to

restrict the two volatility measures to a first lag in delta form plus a lagged level.<sup>15</sup> As for the delta return, we removed the first lag, which appeared to be dominated by the second. However, since the latter had a negative sign, we also tried to remove the second lag, leaving the first in. It turned out that in this case the first lag had a positive coefficient and the model had a better fit than with the second lag only, hence the latter was finally dropped. The resulting model is presented as equation (2) in Table 6.1, where the level of the return volatility, which appeared to be clearly insignificant, has been removed. In this more parsimonious model, the first lag of the moving average of returns appears to have a coefficient very close to one, the first lag of the delta return has a coefficient of 0.12, the delta restriction for the two volatility measures is accepted, while there may be some doubts on the persistence of the level of the volatility of inflation. As far as volatility measures are concerned, the presence of a delta effect suggests that the market is concerned with changes in volatility, whereas it discounts uncertainty contained in past volatility levels.<sup>16</sup> Moreover, dropping the second lag of the dividend and bond yields resulted in the emergence of a clear yield effect with the

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15. Given the way the two measures are calculated, the choice of which lagged level to leave with the delta turned out to be unimportant.

16. Alternatively, one might notice that, since the moving average coefficient in the UK is close to one, the UK equations are close to being in delta returns rather than in levels. However, this would be difficult to reconcile with the absence of additional lags in other regressors.

TABLE 6.1 - UNITED KINGDOM

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EQ(1) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE                  | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|---------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                  | -.312       | 3.019     | 2.544    | -.103   | .000          |
| DY <sub>t</sub>           | 2.197       | 1.891     | 1.977    | 1.162   | .007          |
| DY <sub>t-1</sub>         | 1.620       | 2.005     | 2.712    | .808    | .003          |
| BY <sub>t</sub>           | -2.025      | 1.102     | 1.090    | -1.837  | .017          |
| BY <sub>t-1</sub>         | .477        | 1.094     | 1.225    | .436    | .001          |
| (MSD12r) <sub>t-1</sub>   | 1.119       | .501      | .691     | 2.233   | .024          |
| (MSD12r) <sub>t-2</sub>   | -1.023      | .487      | .636     | -2.112  | .022          |
| (MSD12INF) <sub>t</sub>   | -5.758      | 1.773     | 1.637    | -3.248  | .050          |
| (MSD12INF) <sub>t-1</sub> | 4.928       | 1.821     | 1.632    | 2.706   | .025          |
| (MA12r) <sub>t-1</sub>    | 1.364       | .765      | .714     | 1.784   | .016          |
| (MA12r) <sub>t-2</sub>    | -.514       | .757      | .667     | .679    | .002          |
| $\Delta r_{t-1}$          | .003        | .086      | .090     | .034    | .000          |
| $\Delta r_{t-2}$          | -.121       | .064      | .067     | -1.903  | .018          |

$R^2 = .217$        $\sigma = 6.293$        $F(12,201) = 4.64$  [.0000]      DW = 2.05

LM-Serial Correlation from Lags 1 to 1: F-Form(1,200) = .98 [.3222]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,197) = 2.31 [.0596]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,189)=1.16 [.3182]

ARCH(1): F(1,199) = 2.50 [.1151]

ARCH(4): F(4,193) = 4.43 [.0019] \*\*

ARCH(12): F(12,177) = 1.57 [.1044]

White's Heteroscedasticity Test: F(24,176) = 4.0292 [.0000] \*\*

Jarque-Bera Normality Test:  $\chi^2(2) = 186.507$

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TABLE 6.1 - UNITED KINGDOM

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EQ(2) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE                          | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-----------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                          | -.833       | 2.983     | 2.696    | -.279   | .000          |
| DY <sub>t</sub>                   | 3.876       | .723      | 1.625    | 5.361   | .122          |
| BY <sub>t</sub>                   | -1.469      | .410      | .662     | -3.585  | .059          |
| ( $\Delta$ MSD12r) <sub>t-1</sub> | 1.085       | .449      | .823     | 2.414   | .028          |
| ( $\Delta$ MSD12INF) <sub>t</sub> | -6.120      | 1.722     | 1.832    | -3.555  | .058          |
| (MSD12INF) <sub>t-1</sub>         | -.978       | .568      | .693     | -1.722  | .014          |
| (MA12r) <sub>t-1</sub>            | 1.016       | .273      | .294     | 3.724   | .063          |
| $\Delta r_{t-1}$                  | .120        | .047      | .080     | 2.542   | .030          |

$R^2 = .195$        $\sigma = 6.303$        $F(7,206) = 7.12$  [.0000]      DW = 1.99

LM-Serial Correlation from Lags 1 to 1: F-Form(1,205) = .00 [.9844]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,202) = .74 [.5628]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,194) = .75 [.6990]

ARCH(1): F(1,204) = 3.42 [.0660]

ARCH(4): F(4,198) = 4.73 [.0011] \*\*

ARCH(12): F(12,182) = 1.76 [.0577]

White's Heteroscedasticity Test: F(14,191) = 6.1228 [.0000] \*\*

Jarque-Bera Normality Test:  $\chi^2(2) = 216.368$

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TABLE 6.1 - UNITED KINGDOM

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EQ(3) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE                  | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|---------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                  | 42.571      | 25.988    | 26.313   | 1.638   | .013          |
| DY <sub>t</sub>           | 3.870       | .720      | 1.372    | 5.378   | .124          |
| BY <sub>t</sub>           | -1.669      | .425      | .654     | -3.928  | .070          |
| (ΔMSD12r) <sub>t-1</sub>  | 1.115       | .448      | .584     | 2.490   | .029          |
| (ΔMSD12INF) <sub>t</sub>  | -6.462      | 1.726     | 1.706    | -3.744  | .064          |
| (MSD12INF) <sub>t-1</sub> | -1.642      | .690      | .822     | -2.381  | .027          |
| (MA12r) <sub>t-1</sub>    | 1.206       | .294      | .287     | 4.099   | .076          |
| Δr <sub>t-1</sub>         | .123        | .047      | .066     | 2.620   | .032          |
| LOCUS <sub>t</sub>        | -6.759      | 4.021     | 4.130    | -1.681  | .014          |

$R^2 = .206$        $\sigma = 6.275$        $F(8,205) = 6.64$  [.0000]      DW = 1.98

LM-Serial Correlation from Lags 1 to 1: F-Form(1,204) = .04 [.8415]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,201) = .58 [.6775]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,193) = .69 [.7598]

ARCH(1): F(1,203) = 3.78 [.0532]

ARCH(4): F(4,162) = 5.12 [.0006] \*\*

ARCH(12): F(12,181) = 1.94 [.0320] \*

White's Heteroscedasticity Test: F(16,188) = 5.8129 [.0000] \*\*

Jarque-Bera Normality Test:  $\chi^2(2) = 191.368$

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TABLE 6.1 - UNITED KINGDOM

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EQ(4) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE                | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                | 66.368      | 21.692    | 21.917   | 3.060   | .044          |
| $DY_t$                  | 2.246       | .620      | 1.115    | 3.623   | .061          |
| $BY_t$                  | -1.025      | .359      | .549     | -2.858  | .039          |
| $(\Delta MSD12r)_{t-1}$ | .998        | .372      | .369     | 2.686   | .034          |
| $(\Delta MSD12INF)_t$   | -5.541      | 1.435     | 1.545    | -3.862  | .068          |
| $(MSD12INF)_{t-1}$      | -1.810      | .572      | .695     | -3.163  | .047          |
| $(MA12r)_{t-1}$         | .874        | .246      | .246     | 3.546   | .058          |
| $\Delta r_{t-1}$        | .089        | .039      | .050     | 2.269   | .025          |
| $LOCUS_t$               | -10.625     | 3.358     | 3.457    | -3.164  | .047          |
| $USr_t$                 | .757        | .078      | .108     | 9.698   | .316          |

$R^2 = .456$        $\sigma = 5.204$        $F(9,204) = 19.03$  [.0000]       $DW = 2.03$

LM-Serial Correlation from Lags 1 to 1: F-Form(1,203) = .13 [.7219]  
 LM-Serial Correlation from Lags 1 to 4: F-Form(4,200) = 1.74 [.1425]  
 LM-Serial Correlation from Lags 1 to 12: F-Form(12,192)=1.30 [.2208]  
 ARCH(1): F(1,202) = 5.64 [.0185] \*  
 ARCH(4): F(4,196) = 10.02 [.0000] \*\*  
 ARCH(12): F(12,180) = 5.94 [.0000] \*\*  
 White's Heteroscedasticity Test: F(18,185) = 6.1309 [.0000] \*\*  
 Jarque-Bera Normality Test:  $\chi^2(2) = 39.306$

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TABLE 6.1 - UNITED KINGDOM

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EQ(5) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE                 | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|--------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                 | 1.413       | 2.696     | 2.208    | .524    | .001          |
| DY <sub>t</sub>          | 3.591       | .707      | 1.534    | 5.079   | .111          |
| BY <sub>t</sub>          | -1.662      | .396      | .706     | -4.198  | .079          |
| (ΔMSD12r) <sub>t-1</sub> | 1.166       | .449      | .816     | 2.597   | .032          |
| (ΔMSD12INF) <sub>t</sub> | -5.873      | 1.724     | 1.747    | -3.407  | .053          |
| (MA12r) <sub>t-1</sub>   | .925        | .269      | .295     | 3.439   | .054          |
| Δr <sub>t-1</sub>        | .121        | .047      | .080     | 2.545   | .030          |

$R^2 = .183$        $\sigma = 6.333$        $F(6,207) = 7.73$  [.0000]      DW = 1.99

LM-Serial Correlation from Lags 1 to 1: F-Form(1,206) = .00 [.9846]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,203) = .97 [.4223]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,195) = .97 [.4772]

ARCH(1): F(1,205) = 2.55 [.1119]

ARCH(4): F(4,199) = 5.00 [.0007] \*\*

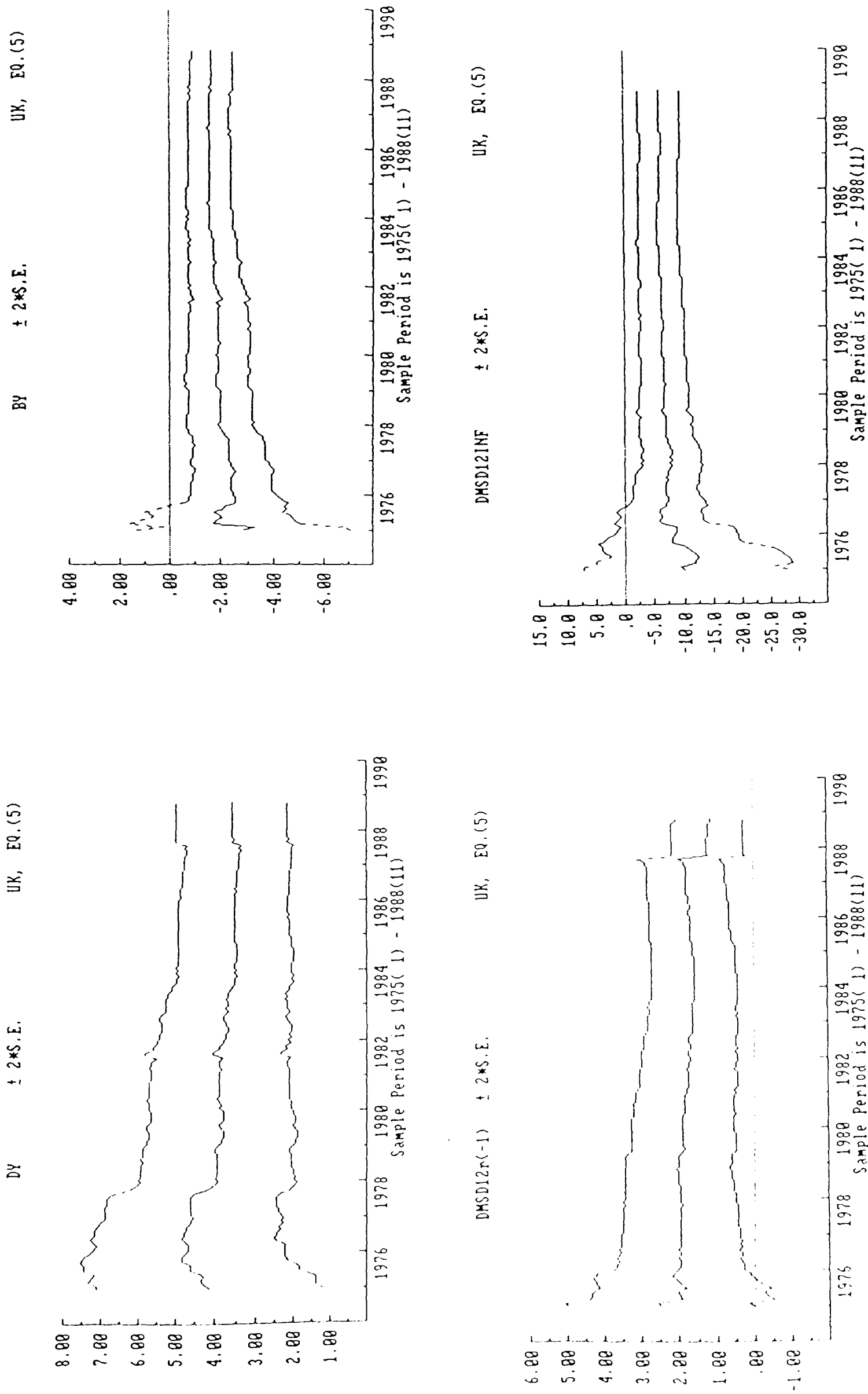
ARCH(12): F(12,183) = 1.83 [.0462] \*

White's Heteroscedasticity Test: F(12,194) = 7.3186 [.0000] \*\*

Jarque-Bera Normality Test:  $\chi^2(2) = 212.030$

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Figure 6.1



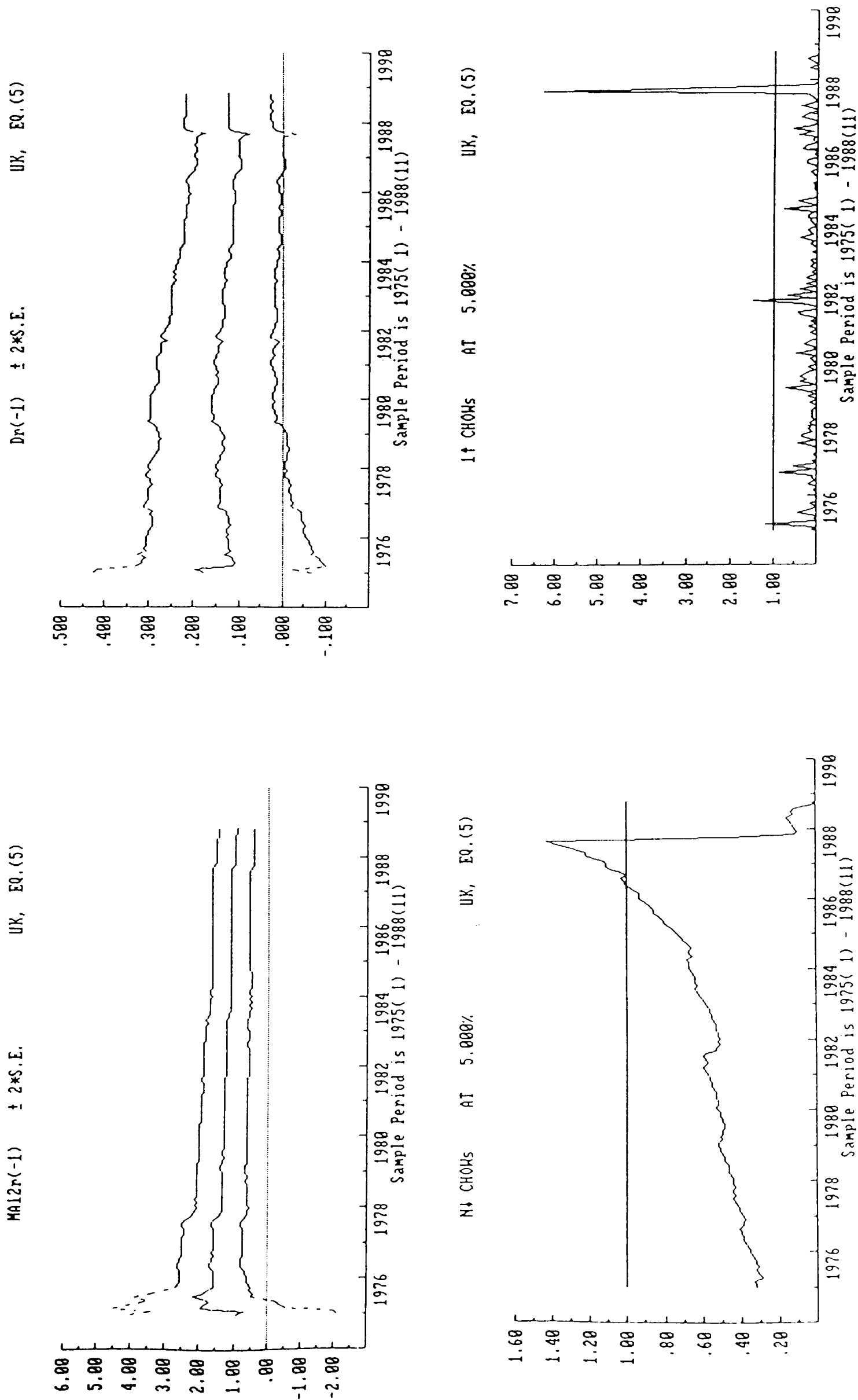


Figure 6.1

TABLE 6.1 - UNITED KINGDOM

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EQ(6) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE                | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                | 1.721       | 2.356     | 2.154    | .730    | .003          |
| $DY_t$                  | 2.121       | .653      | .882     | 3.250   | .049          |
| $BY_t$                  | -1.059      | .357      | .465     | -2.969  | .041          |
| $(\Delta MSD12r)_{t-1}$ | 1.127       | .393      | .659     | 2.870   | .039          |
| $(\Delta MSD12INF)_t$   | -5.115      | 1.513     | 1.444    | -3.380  | .053          |
| $(MA12r)_{t-1}$         | 1.009       | .235      | .255     | 4.291   | .082          |
| $\Delta r_{t-1}$        | .103        | .042      | .063     | 2.466   | .029          |
| 7501                    | 36.730      | 6.126     | 4.422    | 5.995   | .149          |
| 8710                    | -32.041     | 5.614     | 1.193    | -5.707  | .137          |

$R^2 = .383$        $\sigma = 5.532$        $F(8,205) = 15.89$  [.0000]       $DW = 2.29$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,204)=9.51$  [.0023] \*\*

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,201)=2.97$  [.0206] \*

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,193)=1.51$  [.1218]

ARCH(1):  $F(1,204) = .20$  [.6545]

ARCH(4):  $F(4,197) = 1.32$  [.2639]

ARCH(12):  $F(12,181) = .94$  [.5107]

White's Heteroscedasticity Test:  $F(14,191) = 2.9063$  [.0005] \*\*

Jarque-Bera Normality Test:  $\chi^2(2) = 20.387$

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TABLE 6.1 - UNITED KINGDOM

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EQ(7) Modelling  $r_t$  by OLS from 1970(1) to 1988(11)

| VARIABLE   | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------|-------------|-----------|----------|---------|---------------|
| CONSTANT   | 102.082     | 46.162    | 39.160   | 2.211   | .021          |
| TREND      | .033        | .013      | .011     | 2.664   | .031          |
| $\ln IP_t$ | -23.309     | 10.447    | 8.854    | -2.231  | .022          |

$R^2 = .031$        $\sigma = 6.755$        $F(2,224) = 3.55$  [.0304]      DW = 1.83

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EQ(8) Modelling  $r_t$  by OLS from 1970(1) to 1988(11)

| VARIABLE   | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------|-------------|-----------|----------|---------|---------------|
| CONSTANT   | 93.149      | 45.995    | 41.895   | 2.025   | .018          |
| TREND      | .034        | .012      | .011     | 2.700   | .032          |
| $\ln IP_t$ | -22.120     | 10.381    | 9.256    | -2.131  | .020          |
| $DY_t$     | .697        | .328      | .769     | 2.127   | .020          |

$R^2 = .050$        $\sigma = 6.703$        $F(3,223) = 3.91$  [.0095]      DW = 1.80

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TABLE 6.1 - UNITED KINGDOM

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EQ(9) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE                 | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|--------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                 | 87.255      | 52.158    | 52.319   | 1.673   | .014          |
| DY <sub>t</sub>          | 3.426       | .731      | 1.389    | 4.688   | .097          |
| BY <sub>t</sub>          | -1.735      | .408      | .670     | -4.248  | .081          |
| (ΔMSD12r) <sub>t-1</sub> | 1.158       | .449      | .587     | 2.578   | .031          |
| (ΔMSD12INF) <sub>t</sub> | -5.865      | 1.725     | 1.652    | -3.401  | .053          |
| (MA12r) <sub>t-1</sub>   | .673        | .323      | .343     | 2.085   | .021          |
| Δr <sub>t-1</sub>        | .118        | .047      | .067     | 2.501   | .030          |
| TREND                    | .020        | .015      | .013     | 1.359   | .009          |
| lnIP <sub>t</sub>        | -19.046     | 11.571    | 11.590   | -1.646  | .013          |

$R^2 = .194$        $\sigma = 6.322$        $F(8,205) = 6.16$  [.0000]      DW = 2.01

LM-Serial Correlation from Lags 1 to 1: F-Form(1,204) = .02 [.8912]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,201) = 1.19 [.3153]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,193) = 1.97 [.3721]

ARCH(1): F(1,203) = 2.49 [.1164]

ARCH(4): F(4,197) = 5.31 [.0004] \*\*

ARCH(12): F(12,181) = 2.02 [.0245] \*

White's Heteroscedasticity Test: F(16,188) = 5.9339 [.0000] \*\*

Jarque-Bera Normality Test:  $\chi^2(2) = 205.253$

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expected signs. Notice that the values of the coefficients of the two yield measures do not encourage the reverse yield gap restriction, which is in fact accepted only at the expense of a considerable deterioration in fit. Also, the emergence of a level effect in the two yields suggests that the two variables are stationary or, alternatively, that they are non stationary but cointegrated. The latter hypothesis turned out to be supported by the data (see Appendix A.1).

Equation (3) differs from (2) in that the log ratio between the UK and US real prices is added to the regressors. Notice that, although the coefficient appears to have the expected negative sign, there are some doubts about its significance. Interestingly, if the sample period is limited to 1985(12), the coefficient becomes higher in absolute terms (equal to -10.02, with a t-statistic of -2.24). This result has no easy interpretation, since the integration between the UK and the US markets did, if anything, increase after 1985. However, the existence of a close relationship between the two markets is confirmed in equation (4), in which the current US real return<sup>17</sup> has been added to the regressors of equation (3). Since  $USr_t$  is not available at the beginning of time  $t$ , its significance in equation (4) does not contradict the EMT. But the equation shows that, although the values of the lagged regressors are affected by the presence of  $USr_t$ , their significance in our equations is quite

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17. Again,  $USr_t$  has not been corrected for exchange rate variations. See footnote 9.

independent of the contemporaneous relationship between the two markets. Hence controlling for a such relationship does not invalidate our results. Far from this, the presence of  $USr_t$  actually restores the significance of  $LOCUS_t$  and the lagged inflation volatility level even after 1985.

Equation (5), in which both  $LOCUS_t$  and the lagged inflation volatility level have been dropped, represents our most parsimonious model choice. Nonetheless, diagnostic testing reveals that the estimates are affected by a considerable degree of heteroscedasticity. Test results show that heteroscedasticity is due to the dependence of the squared residuals on their own second lag (ARCH test) and/or on the dividend yield and its square and the square of the lagged delta return (White's test). In addition, the Jarque-Bera test clearly rejects the normality assumption for the conditional distribution of returns. On the face of these results, we tried to investigate whether heteroscedasticity and non-normality could be materially accounted for by the presence of a few anomalous return values within the sample period. We followed this route, rather than seeking normalising and variance-stabilising transformations of the variables, since the latter would have disturbed the interpretation of our results. Hence in equation (6) two dummy variables were added to the regressors, in order to remove the two largest monthly returns of opposite sign: the 40.8% rise in

1975(1) and the -30.5% crash of 1987(10).<sup>18</sup> Results were mildly encouraging. In the presence of the two dummies, the ARCH tests cannot reject homoscedasticity, although at the same time first-order autocorrelation in the levels of residuals is introduced. On the other hand, the White test still rejects homoscedasticity, due to the dependence of the squared residuals on the square of the delta return. As for non-normality, although the introduction of the two dummies partially alleviates the problem, the Jarque-Bera test still comfortably rejects the normality assumption. This leaves us relying on asymptotic theory to justify our results. In this regard, notice that, even using heteroscedasticity-corrected standard errors, only the delta return and the return volatility, among the regressors in equations (5) and (6), have t-statistics lower than 2, and that, in the presence of the two dummies, the two t values grow from -1.51 to -1.63 and from 1.43 to 1.71 respectively.

On the whole, one should feel sufficiently comfortable about the robustness of our estimation results. Indeed, there can be little doubt that our equations provide enough evidence against the hypothesis that current returns in the UK stock market are independent of publicly available past information. In order to dispel the suspicion that results may be simply due to a sample selection bias, recursive least squares coefficients of equation (5) are presented in the graphs in Figure 6.1. These show that the

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18. Remember that, in our notation, the two dummies are in fact at 1974(12) and 1987(9).

estimated coefficients are reasonably stable over the sample period, although 1-step forecast tests (1 $\uparrow$  Chows) and the sequence of breakpoint F-tests (N $\downarrow$  Chows) indicate the presence of important structural breakdowns, coinciding with the largest return outliers, such as the October 1987 crash, which is also reflected in a significant jump in some of the recursive coefficients.

As for the interpretation of our results, we are inclined to regard return predictability as evidence in favour of the conventional view of stock market behaviour, outlined in the previous chapter. However, we know that, before endorsing such a conclusion, we need to test for the alternative hypothesis that predictability can be explained by time-varying expected returns, since in this case our results would be entirely consistent with the EMT. Of course, one can hardly hope to gather conclusive evidence on this subject. For example, the significance of our lagged variables in equations which include the risk proxy defined in (6.1) could be taken as evidence against the EMT. However, one could also say that (6.1) is just a poor measure of true uncertainty and that, if a good measure could be found, all the other coefficients would turn to zero. In fact, there is no such a thing as conclusive evidence, especially in economics. All we can do is try to give alternative hypotheses a fair chance to contradict our results. To this end, we shall adopt one particular EMT model with variable expected returns, which has recently been presented as a suitable candidate for the purpose of accommodating

return predictability within the EMT. The model, developed by Balvers et al. (1990), has already been examined in Chapters 3 and 4. We saw in Chapter 3 that the model predicts the existence of an inverse relationship between current stock returns and lagged output, which can be reconciled with the EMT within the framework of a production-based CAPM. Balvers et al. use their model to explain why dividend yields have been found to be good predictors of stock returns. Their theory is that the dividend yield simply mirrors the output effect and that, as a consequence, it should disappear once output is included among the regressors. The empirical evidence presented in their paper seems to be in line with this conclusion. The relationship is tested on US, UK, Japanese and Canadian data, and in all cases the dividend yield, which appears to predict returns when regressed in isolation, disappears as soon as industrial production, along with a trend, is added to regressors. We have seen in Chapter 4 that the same conclusion is not supported by Italian data. In addition, we have argued that the inclusion of a trend among the regressors is not a recommendable choice, since stock returns are clearly stationary in the mean. Nevertheless, the paper presents a serious challenge to our interpretation of return predictability as evidence against the EMT. Indeed, equation (7) in Table 6.1 shows that the predicted relationship between stock returns and lagged output (including a trend) holds on UK data even at monthly frequencies. Furthermore, when in equation (8) the dividend yield is

used as an additional regressor, it behaves exactly as predicted by Balvers et al., in that its coefficient becomes much smaller (compared to, say, equation (5)) and in fact loses its significance (using H.C.S.E.). In the typical fashion of EMT testing routines - where you win if you lose - Balvers et al. would stop here and claim that return predictability is consistent with the EMT. But such a conclusion would be quite wrong. What Balvers et al. should have done is what practitioners normally do, i.e. look at dividend yields not in isolation, but in their relation to bond yields. As discussed above, this is common practice among investment managers, who look at the gap (or the ratio) between stock and bond yields in order to evaluate the relative attractiveness of the underlying asset classes. Had they done that, Balvers et al. would have noticed that not only dividend and bond yields are jointly significant, but also that the output plus trend effect completely disappears. This can be seen on UK data in equation (9), where lagged industrial production and trend have been added to the regressors of our parsimonious model, equation (5). Notice that the estimated coefficients are hardly at all affected by the inclusion of the two additional regressors, for the simple reason that both industrial production and trend become quite insignificant within the model.<sup>19</sup> As it turns out, the two additional

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19. A similar result is presented in Attanasio (1989), where time-varying expected returns are modelled using a GARCH process for volatility. The paper shows that, while the dividend yield on its own is insignificant when used as an additional regressor along with GARCH volatility (see Attanasio and Wadhvani (1989)), adding the Treasury Bill rate and inflation makes the three variables jointly significant.

variables remain insignificant even when the change in return volatility - itself a proxy for time-varying expected returns - is dropped from equation (9). On the other hand, they reacquire significance if the moving average of past returns is dropped. This suggests that the output plus trend effect may in fact be merely proxying for momentum, rather than for time-varying expected returns. But then it would be more correct to say that the trend on its own is a proxy for momentum (although not as good a proxy as the return moving average), since in all our equations, in the UK as well as in the other countries, lagged industrial production is never significant without including a trend. This fact should cast serious doubts on the overall results presented in Balvers et al..

We conclude that our UK evidence cannot be explain away by Balvers et al.'s version on the production-based CAPM. As we shall presently see, a similar conclusion can be drawn about our models for the US, Japan and Italy.

#### United States

Table 6.2 contains results obtained on the US data. Equation (1) presents the general model, which is identical to Equation (1) in the UK Table. The only prominent feature in the equation seems to be the appearance of a delta effect in the bond yield and, possibly, of a level or delta effect in the dividend yield. Otherwise, the

equation does not seem to have much in common with its UK counterpart. However, a little effort in specification search turns out to be sufficient to improve on such a first-cut result.

In equation (2) the second lag of the return and inflation volatility measures, and the second lag of the moving average of returns and of the delta return have been dropped from the model. We dropped second lags despite the fact that, in the case of the moving average and the moving standard deviation of returns, second lags dominate first lags in the general model. Given the way these variables are constructed, however, successive lags are in fact highly correlated and, in the absence of a delta effect, estimates are very sensitive to the simultaneous presence of two lags in the same equation. In such a case we chose to keep the most recent lag, which has a more obvious interpretation, rather than the second lag, despite the fact that the latter would provide a better fit. Such modifications produce a model which is much more similar to equation (5) in the UK Table 6.1. Notice that in both models the moving average term has the expected positive sign, although the US coefficient appears to be lower than one. The US delta return also has a positive coefficient, with a magnitude comparable to its UK counterpart and a slightly higher heteroscedasticity-corrected t-statistic of 1.60. An important difference between the two equations is the presence in the US model of a level rather than a delta effect in the two volatility measures and of a delta rather than a level

TABLE 6.2 - UNITED STATES

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EQ(1) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE           | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|--------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT           | -5.702      | 2.088     | 1.968    | -2.731  | .036          |
| $DY_t$             | 4.450       | 2.978     | 3.288    | 1.511   | .011          |
| $DY_{t-1}$         | -2.861      | 2.939     | 3.204    | -.973   | .005          |
| $BY_t$             | -3.344      | .919      | .937     | -3.639  | .062          |
| $BY_{t-1}$         | 3.103       | .918      | .915     | 3.379   | .054          |
| $(MSD12r)_{t-1}$   | .282        | .597      | .907     | .473    | .001          |
| $(MSD12r)_{t-2}$   | .338        | .592      | .838     | .572    | .002          |
| $(MSD12INF)_t$     | -3.560      | 3.365     | 3.407    | -1.058  | .006          |
| $(MSD12INF)_{t-1}$ | 1.520       | 3.419     | 3.479    | .445    | .001          |
| $(MA12r)_{t-1}$    | -.314       | .835      | .921     | -.376   | .001          |
| $(MA12r)_{t-2}$    | .966        | .820      | .832     | 1.179   | .007          |
| $\Delta r_{t-1}$   | .104        | .092      | .097     | 1.135   | .006          |
| $\Delta r_{t-2}$   | -.006       | .069      | .072     | -.091   | .000          |

$R^2 = .141$        $\sigma = 4.601$        $F(12,201) = 2.75$  [.0018]       $DW = 1.96$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,200) = .43$  [.5105]

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,197) = .36$  [.8398]

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,189) = .60$  [.8413]

ARCH(1):  $F(1,199) = 5.23$  [.0233 \*]

ARCH(4):  $F(4,193) = 1.40$  [.2368]

ARCH(12):  $F(12,177) = 1.18$  [.3042]

White's Heteroscedasticity Test:  $F(24,176) = 2.9753$  [.0000] \*\*

Jarque-Bera Normality Test:  $\chi^2(2) = 29.453$

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TABLE 6.2 - UNITED STATES

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EQ(2) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE         | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT         | -5.305      | 2.015     | 1.963    | -2.633  | .033          |
| $DY_t$           | 5.952       | 2.275     | 2.726    | 2.616   | .032          |
| $DY_{t-1}$       | -4.428      | 2.185     | 2.571    | -2.027  | .020          |
| $BY_t$           | -3.414      | .906      | .961     | -3.770  | .065          |
| $BY_{t-1}$       | 3.203       | .902      | .940     | 3.553   | .065          |
| $(MSD12r)_{t-1}$ | .586        | .221      | .238     | 2.644   | .033          |
| $(MSD12INF)_t$   | -2.078      | .815      | .845     | -2.548  | .031          |
| $(MA12r)_{t-1}$  | .623        | .277      | .323     | 2.250   | .024          |
| $\Delta r_{t-1}$ | .101        | .064      | .063     | 1.581   | .012          |

$R^2 = .133$        $\sigma = 4.576$        $F(8,205) = 3.94$  [.0002]       $DW = 1.98$

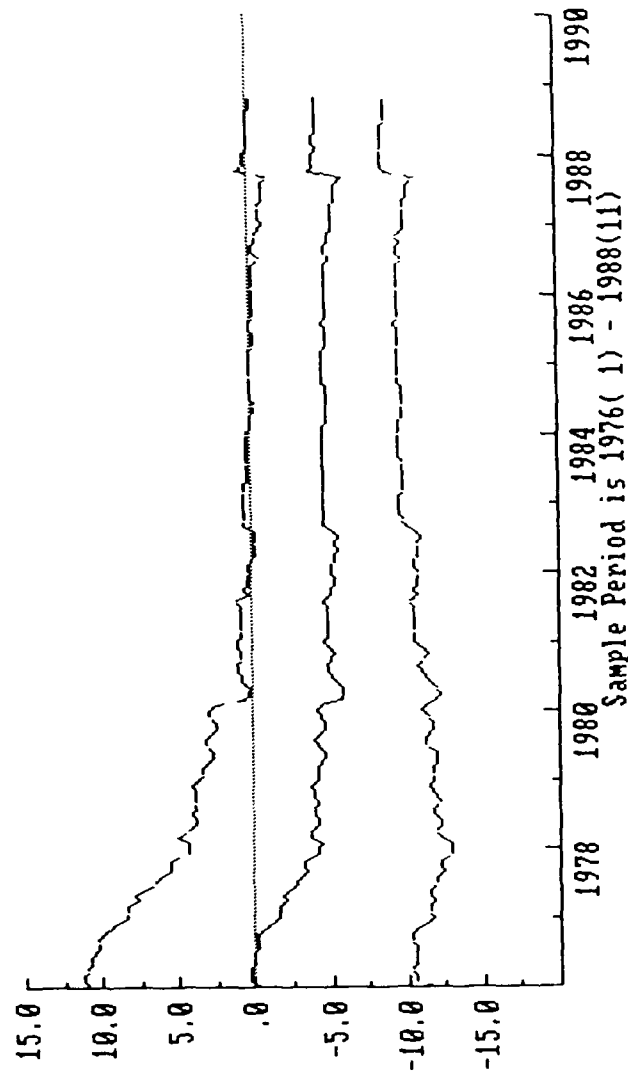
LM-Serial Correlation from Lags 1 to 1: F-Form(1,204) = .07 [.7948]  
LM-Serial Correlation from Lags 1 to 4: F-Form(4,201) = .23 [.9206]  
LM-Serial Correlation from Lags 1 to 12: F-Form(12,193)= .65 [.7980]  
ARCH(1): F(1,203) = 6.16 [.0139] \*  
ARCH(4): F(4,197) = 1.67 [.1584]  
ARCH(12): F(12,181) = 1.27 [.2404]  
White's Heteroscedasticity Test: F(16,188) = 3.6766 [.0000] \*\*  
Jarque-Bera Normality Test:  $\chi^2(2) = 37.119$

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US, EQ.(2)

$\pm 2*S.E.$

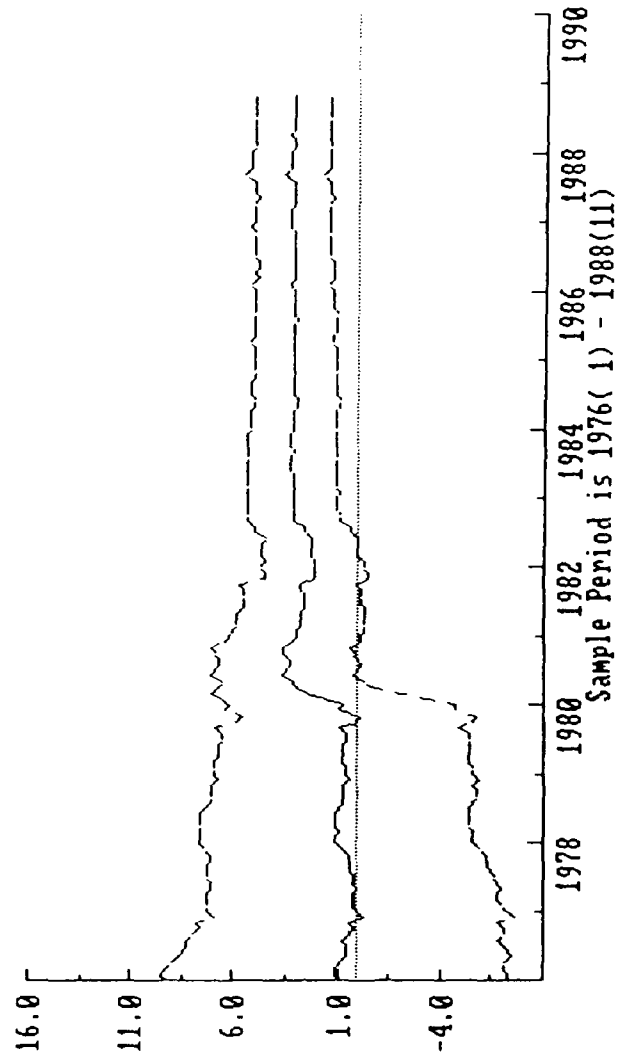
DY(-1)



US, EQ.(2)

$\pm 2*S.E.$

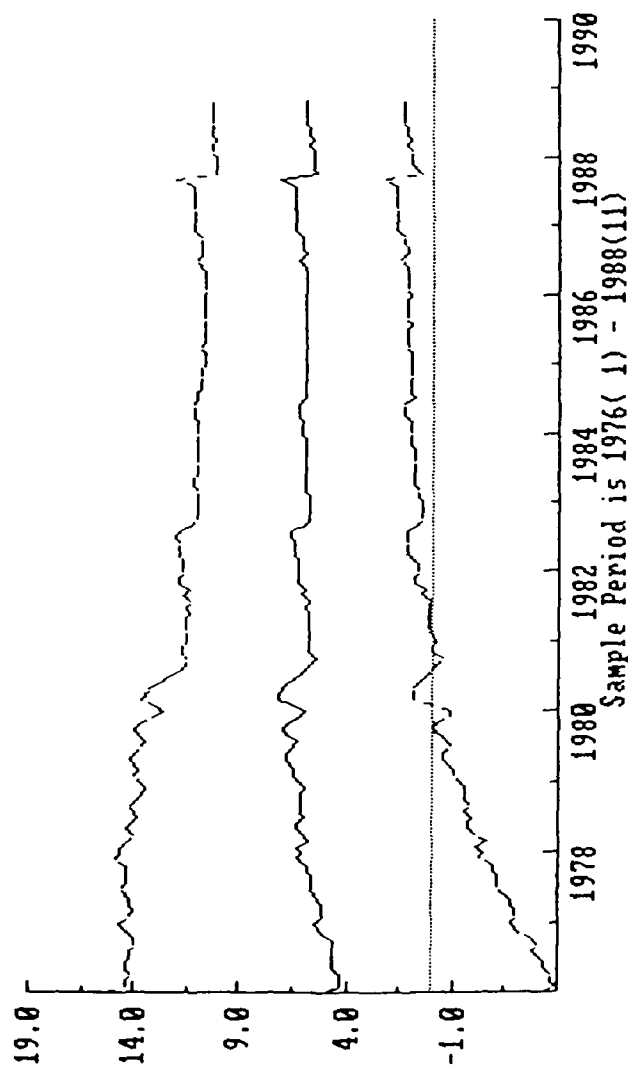
BY(-1)



US, EQ.(2)

$\pm 2*S.E.$

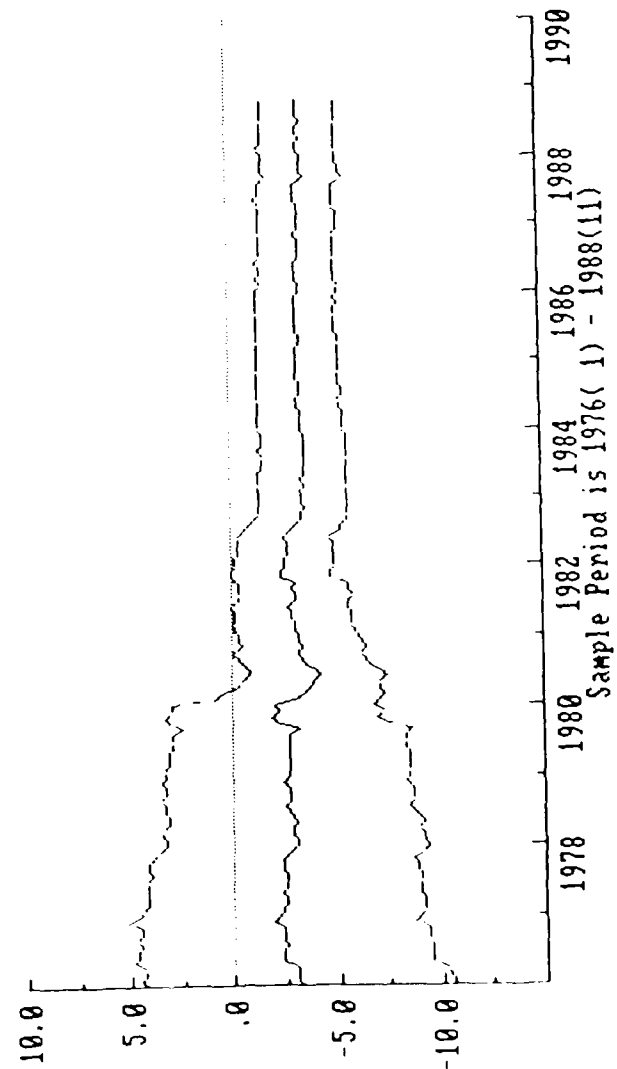
DY

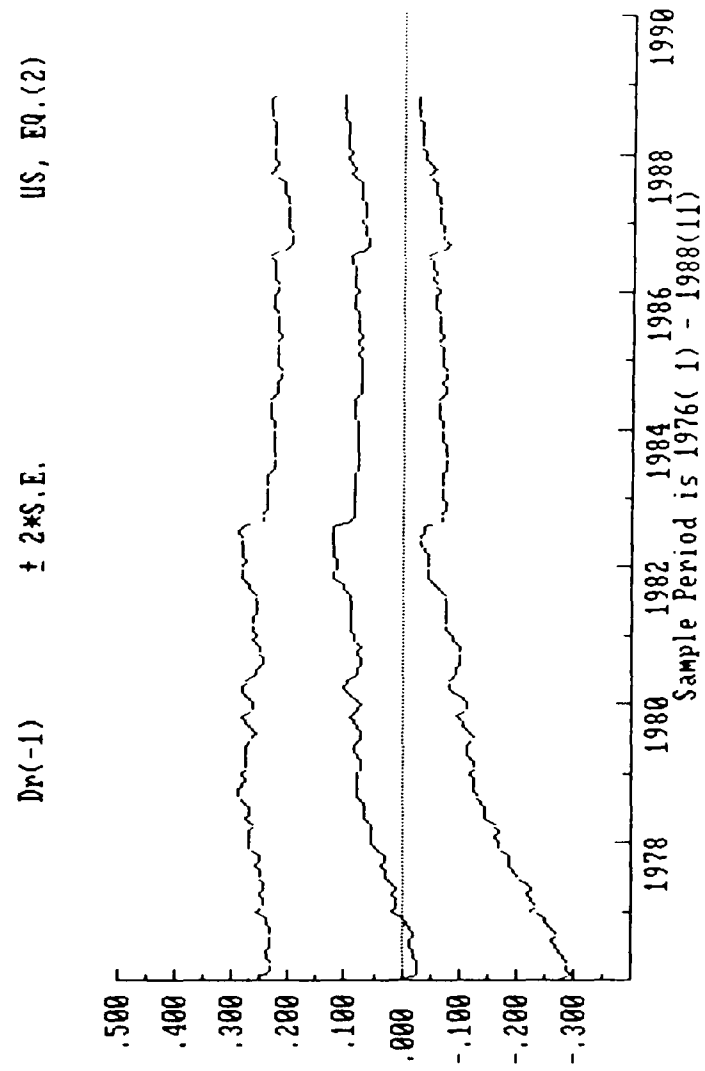
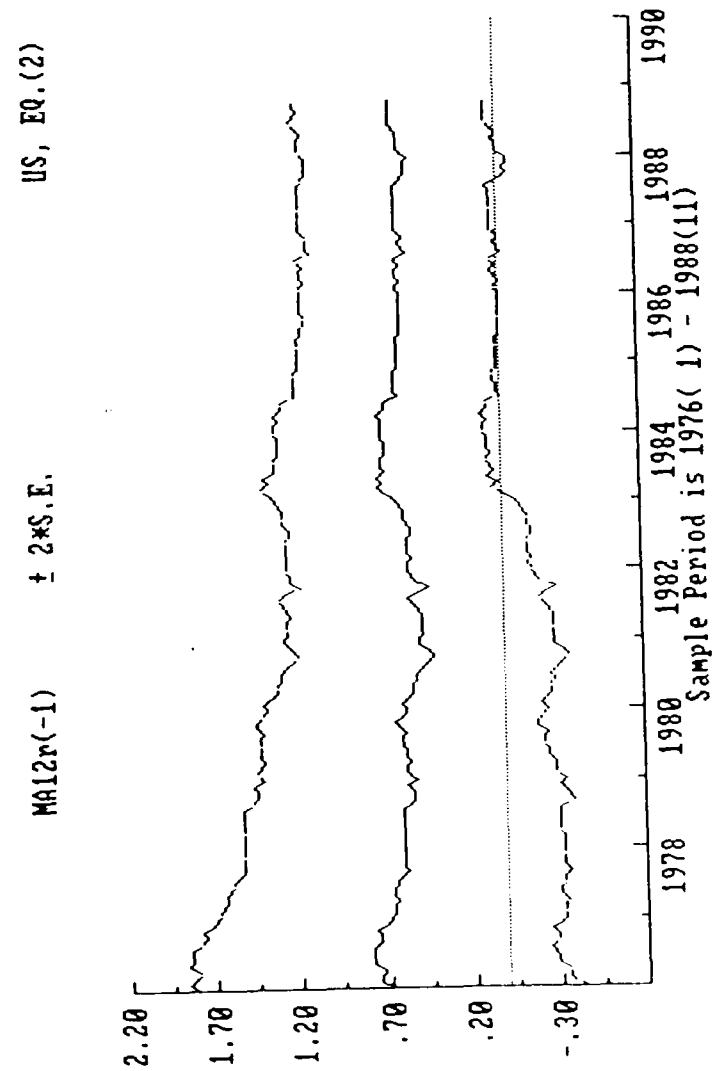
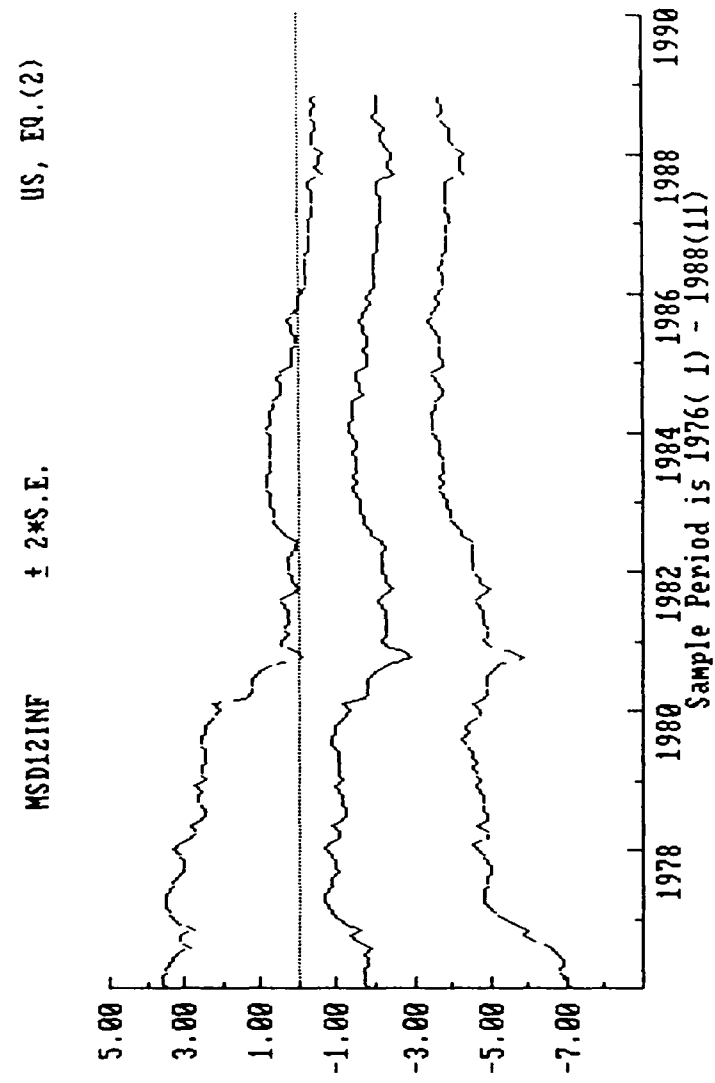
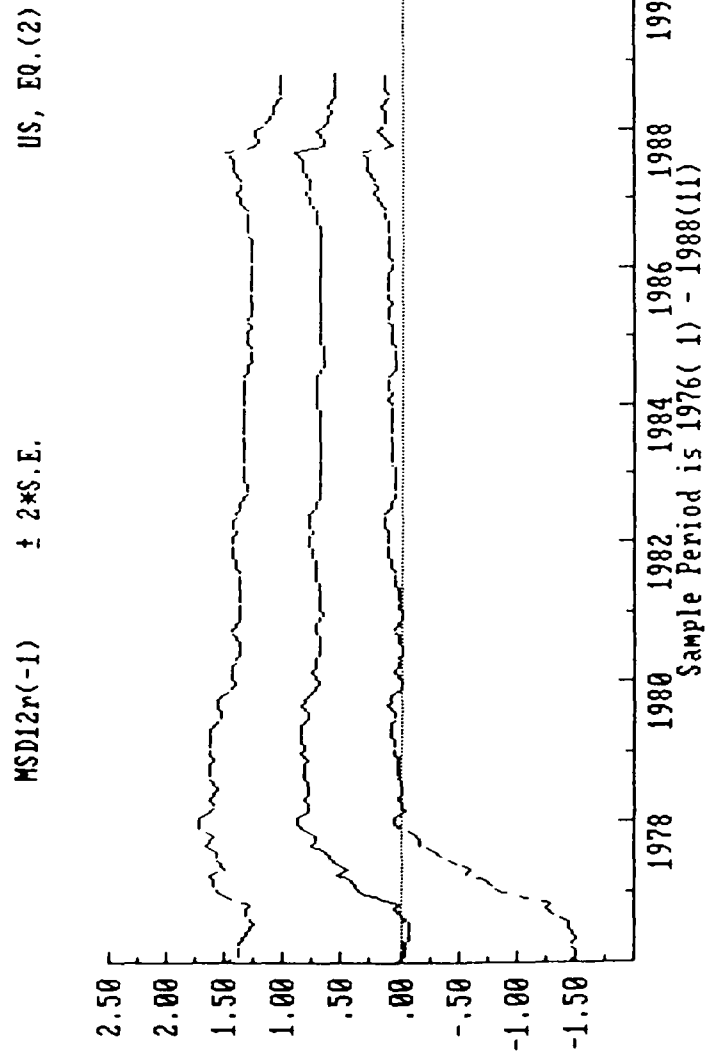


US, EQ.(2)

$\pm 2*S.E.$

BY





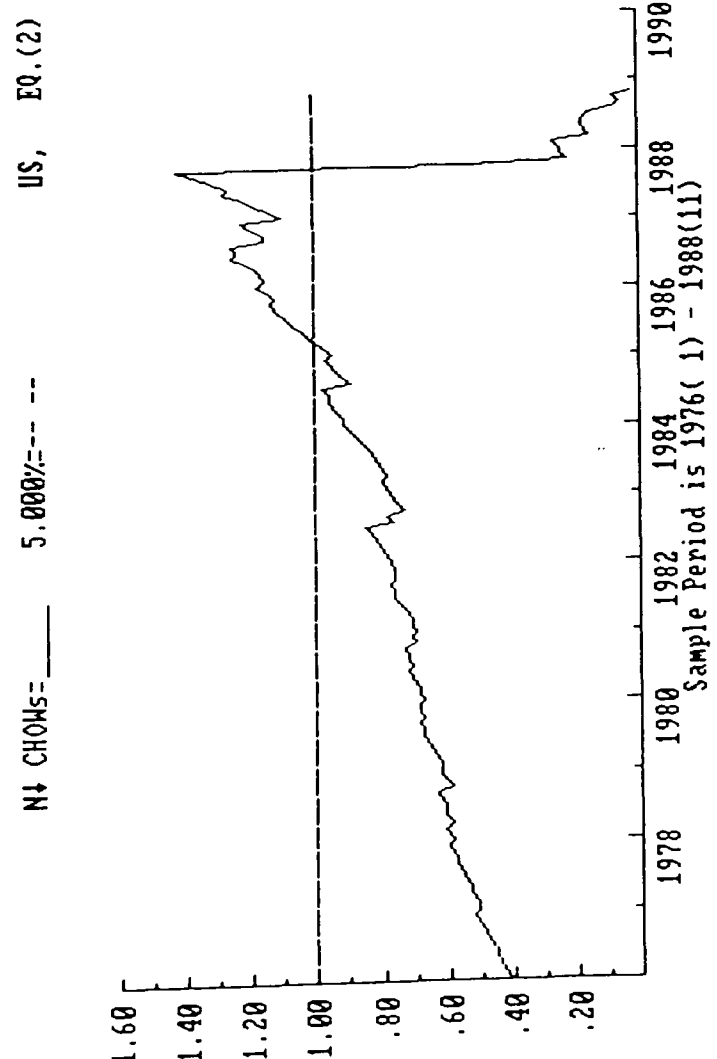
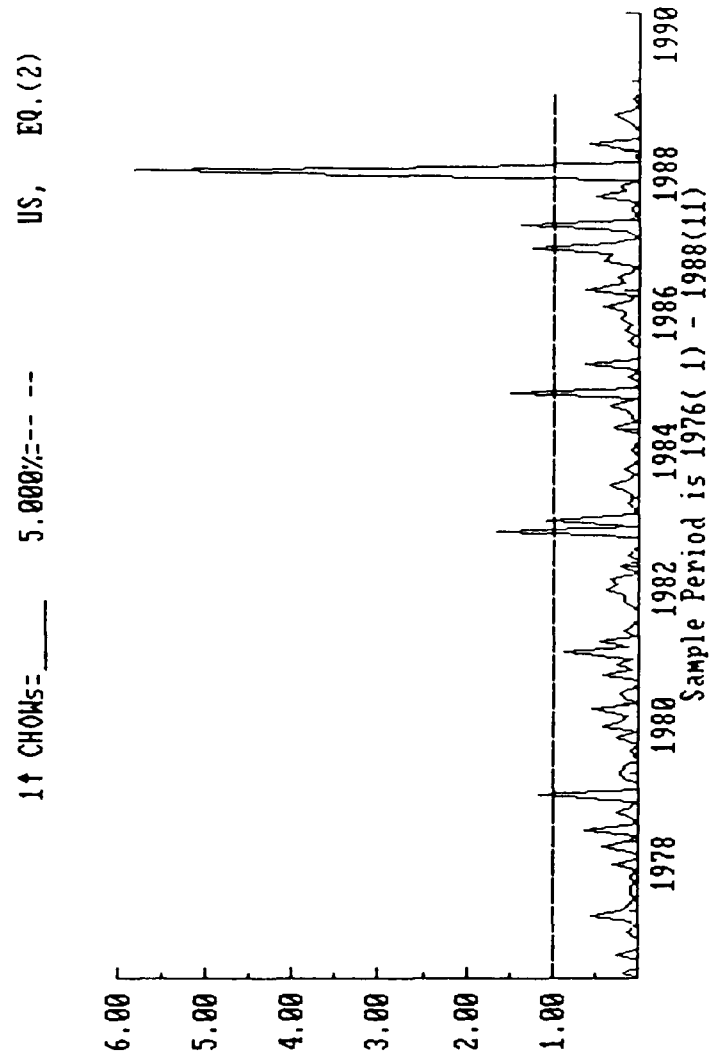


TABLE 6.2 - UNITED STATES

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EQ(3) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE         | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT         | -5.443      | 2.012     | 2.036    | -2.706  | .034          |
| $\Delta Y_t$     | 5.486       | 2.235     | 2.851    | 2.455   | .028          |
| $DY_{t-1}$       | 1.119       | .385      | .410     | 2.904   | .039          |
| $\Delta BY_t$    | -3.289      | .899      | 1.025    | -3.661  | .061          |
| $(MSD12r)_{t-1}$ | .577        | .221      | .251     | 2.608   | .032          |
| $(MSD12INF)_t$   | -2.120      | .815      | .879     | -2.601  | .032          |
| $(MA12r)_{t-1}$  | .522        | .261      | .333     | 2.001   | .019          |
| $\Delta r_{t-1}$ | .099        | .064      | .065     | 1.545   | .011          |

$R^2 = .128$        $\sigma = 4.578$        $F(7,206) = 4.33$  [.0002]       $DW = 1.99$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,205) = .04$  [.8402]  
LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,202) = .24$  [.9159]  
LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,194) = .72$  [.7318]  
ARCH(1):  $F(1,204) = 6.51$  [.0115] \*  
ARCH(4):  $F(4,198) = 1.68$  [.1561]  
ARCH(12):  $F(12,182) = 1.27$  [.2414]  
White's Heteroscedasticity Test:  $F(14,191) = 3.8998$  [.0000] \*\*  
Jarque-Bera Normality Test:  $\chi^2(2) = 39.629$

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TABLE 6.2 - UNITED STATES

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EQ(4) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE         | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT         | -4.795      | 1.867     | 1.884    | -2.568  | .032          |
| $\Delta Y_t$     | 3.808       | 2.150     | 2.399    | 1.771   | .015          |
| $DY_{t-1}$       | 2.678       | 2.060     | 2.306    | -1.300  | .008          |
| $BY_t$           | -2.696      | .846      | .861     | -3.186  | .048          |
| $BY_{t-1}$       | 2.593       | .840      | .869     | 3.086   | .045          |
| $(MSD12r)_{t-1}$ | .549        | .205      | .236     | 2.679   | .034          |
| $(MSD12INF)_t$   | -1.696      | .759      | .764     | -2.235  | .024          |
| $(MA12r)_{t-1}$  | .774        | .258      | .307     | 3.000   | .042          |
| $\Delta r_{t-1}$ | .063        | .060      | .058     | 1.062   | .006          |
| 7410             | 16.268      | 4.491     | 1.972    | 3.623   | .061          |
| 8710             | -21.632     | 4.355     | 1.106    | -4.967  | .108          |

$R^2 = .266$        $\sigma = 4.233$        $F(10,203) = 7.35$  [.0000]       $DW = 2.07$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,202) = 1.00$  [.3185]

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,199) = .63$  [.6445]

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,191)=1.38$  [.1804]

ARCH(1):  $F(1,201) = .98$  [.3235]

ARCH(4):  $F(4,195) = 1.00$  [.4088]

ARCH(12):  $F(12,179) = 1.42$  [.1615]

White's Heteroscedasticity Test:  $F(18,184) = 1.7812$  [.0303] \*

Jarque-Bera Normality Test:  $\chi^2(2) = 3.011$

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TABLE 6.2 - UNITED STATES

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EQ(5) Modelling  $r_t$  by OLS from 1970(1) to 1988(11)

| VARIABLE   | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------|-------------|-----------|----------|---------|---------------|
| CONSTANT   | 96.008      | 28.755    | 28.091   | 3.339   | .047          |
| TREND      | .058        | .016      | .016     | 3.572   | .054          |
| $\ln IP_t$ | -23.344     | 6.955     | 6.807    | -3.357  | .048          |

$R^2 = .054$        $\sigma = 4.749$        $F(2,224) = 6.40$  [.0020]       $DW = 1.95$

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EQ(6) Modelling  $r_t$  by OLS from 1970(1) to 1988(11)

| VARIABLE   | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------|-------------|-----------|----------|---------|---------------|
| CONSTANT   | 95.668      | 28.665    | 27.855   | 3.337   | .048          |
| TREND      | .057        | .016      | .016     | 3.556   | .054          |
| $\ln IP_t$ | -23.772     | 6.938     | 6.755    | -3.426  | .050          |
| $DY_t$     | .535        | .344      | .426     | 1.555   | .011          |

$R^2 = .064$        $\sigma = 4.734$        $F(3,223) = 5.10$  [.0020]       $DW = 1.93$

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TABLE 6.2 - UNITED STATES

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EQ(7) Modelling  $r_t$  by OLS from 1971(2) to 1988(11)

| VARIABLE         | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT         | 99.981      | 38.690    | 38.086   | 2.584   | .032          |
| $DY_t$           | 6.269       | 2.260     | 2.725    | 2.775   | .037          |
| $DY_{t-1}$       | -4.870      | 2.181     | 2.547    | -2.233  | .024          |
| $BY_t$           | -3.062      | .903      | .919     | -3.391  | .054          |
| $BY_{t-1}$       | 2.695       | .922      | .949     | 2.924   | .040          |
| $(MSD12r)_{t-1}$ | .202        | .284      | .326     | .712    | .002          |
| $(MSD12INF)_t$   | -2.082      | .870      | 1.016    | -2.393  | .027          |
| $(MA12r)_{t-1}$  | .160        | .335      | .385     | .477    | .001          |
| $\Delta r_{t-1}$ | .118        | .064      | .066     | 1.855   | .017          |
| TREND            | .062        | .024      | .025     | 2.556   | .031          |
| $\ln IP_t$       | -24.741     | 9.075     | 8.953    | -2.726  | .035          |

$R^2 = .164$        $\sigma = 4.517$        $F(10,203) = 3.98$  [.0001]       $DW = 1.98$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,202) = .15$  [.7010]

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,199) = .30$  [.8763]

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,191) = .70$  [.7497]

ARCH(1):  $F(1,201) = 5.51$  [.0199] \*

ARCH(4):  $F(4,195) = 1.52$  [.1972]

ARCH(12):  $F(12,179) = 1.27$  [.2390]

White's Heteroscedasticity Test:  $F(20,182) = 3.1923$  [.0000] \*\*

Jarque-Bera Normality Test:  $\chi^2(2) = 41.849$

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effect in the dividend and bond yields. This result is not inconsistent with our assumptions. Although, of course, we would like to observe as large a similarity as possible between the two models, we should at the same time let the data reflect factual differences between different markets. In regard to volatility measures, our estimates suggest that US investors are concerned with volatility levels, rather than, as in the UK, with changes in volatility. As for dividend and bond yields, the available evidence suggests a rejection of the hypothesis of cointegration between the two variables (see Appendix A.1), thus justifying their presence in delta form in the US equations. The delta restriction is actually carried out in equation (3) and appears to be accepted by the data, although the level of  $DY_{t-1}$  has to be kept in the equation. While compatible with the delta restriction for  $DY_t$ , this result suggests that the relevant change in the dividend yield may be shorter than one month.

Heteroscedasticity in the US equations is not as large as it is in the UK equations. First-order ARCH is detected in equations (2) and (3), while White's test attributes heteroscedasticity to  $DY_{t-1}$  and its square and the square on the moving average of returns. The Jarque-Bera test also rejects normality, although the test values are not as extreme as in the UK. Again, we checked whether excluding the two largest opposite outliers may lead to improved results. Hence in equation (4) two dummies remove the largest positive return (1974(10)=15.3%) and the largest negative return (1987(10)=-24.2%).

As a consequence, both A.R.C.H. and non-normality are rejected, but the delta return (and perhaps dividend yields) disappear from the model.

The recursive least squares coefficients of equation (2) are presented in Figure 6.2. Again, the coefficients appear to be rather stable over time, despite the presence of relevant jumps coinciding with the October 1987 crash and other extreme return values.

Finally, tests of the alternative hypothesis of time-varying expected returns present results similar to the UK ones. Equation (5) shows that, just as reported by Balvers et al., the output plus trend effect is significant, even on monthly data. In turn, equation (6) shows that the dividend yield is clearly insignificant as an additional regressor. However, when in equation (7) industrial production and trend are added to the regressors of equation (2) the picture changes. In contrast with the production-based CAPM, in (7) dividend and bond yields remain significant, along with inflation volatility. Unlike in the UK, however, the output plus trend effect is also significant and actually dislodges return volatility and the moving average of returns from the equation. This might suggest a role for the effect as a useful predictor of stock returns. But we prefer to resist such a conclusion since, as in the UK, industrial production is never significant on its own, but only if a trend is included.

## Japan

The results presented in Tables 6.1 and 6.2 should have reached the purpose of casting some doubts on the traditional efficiency view. Moreover, the fact that our evidence applies to the UK and the US markets - two markets for which informational efficiency is usually regarded as a well-established empirical fact - makes it all the more intriguing. Especially for the US the EMT has been 'confirmed' so many times and in so many fashions that its rejection may perhaps suggest a similar and possibly more powerful rejection in other markets, whose reputation for efficiency is not as solid. Such an expectation would however be unwarranted, as it neglects the fact that, even though return predictability may be a sign of inefficiency, the reverse is not necessarily true. In other words, our results should not be interpreted as a measure of the degree of inefficiency of different markets, but only as an attempt to identify some basic properties of their conventional structure. In this regard, it is rather the presence of fundamental variables, like dividend and bond yields and the two volatility measures, which gives us an idea of the importance of fundamental information in the return generation process in each market. Remember that we are not disputing the obvious fact that fundamental information plays a substantial role in this process, but only that such a role does not conform to the predictions of the EMT. Hence the significance of lagged

fundamental variables - as presented in our UK and US equations - should indeed be interpreted as a sign of greater relative efficiency, provided that such a term is only used to denote a reasonably stable association between stock prices and fundamental values, rather than the strict identity of the two, as predicted by the EMT.

Our remarks should become clearer by looking at Table 6.3, which contains our results on the Japanese market. As we noticed earlier, equation (1) in the table is exactly what a traditional EMT advocate would expect: none of the lagged variables seems to have any significance as a predictor of current returns. Does this mean that we should stop the analysis and proclaim the Japanese market an epitome of informational efficiency? Not in the least. In fact, if experience and common sense have a role to play in empirical research, one should look for shorter trend lags and longer fundamental lags in the Japanese market. This is exactly what we have done, and the result appears in equation (2). Here the 12-month moving average and the delta returns have been removed, and two further lags of each variable have been added to regressors, along with three lags of the stock return itself and four lags of  $LOCUSM_t$ , defined as the deviation of the log price ratio  $LOCUS_t$  from its 12-month moving average. Such detrending operation (which was not required for  $LOCUS_t$  in the UK) has been necessary to remove a

TABLE 6.3 - JAPAN

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EQ(1) Modelling  $r_t$  by OLS from 1973(1) to 1988(11)

| VARIABLE                  | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|---------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                  | 7.377       | 3.335     | 3.242    | 2.212   | .027          |
| DY <sub>t</sub>           | 6.073       | 7.257     | 7.611    | .837    | .004          |
| DY <sub>t-1</sub>         | -6.266      | 7.193     | 7.479    | -.871   | .004          |
| BY <sub>t</sub>           | -1.154      | 1.079     | 1.300    | -1.069  | .006          |
| BY <sub>t-1</sub>         | .588        | 1.067     | 1.207    | .551    | .002          |
| (MSD12r) <sub>t-1</sub>   | -.581       | .692      | .654     | -.841   | .004          |
| (MSD12r) <sub>t-2</sub>   | .336        | .709      | .665     | .474    | .001          |
| (MSD12INF) <sub>t</sub>   | -.156       | 1.311     | 1.361    | -.119   | .000          |
| (MSD12INF) <sub>t-1</sub> | -.594       | 1.311     | 1.458    | -.453   | .001          |
| (MA12r) <sub>t-1</sub>    | .510        | .868      | .864     | .587    | .002          |
| (MA12r) <sub>t-2</sub>    | -.832       | .841      | .835     | -.989   | .006          |
| $\Delta r_{t-1}$          | .037        | .087      | .094     | .423    | .001          |
| $\Delta r_{t-2}$          | .026        | .068      | .082     | .377    | .001          |

$R^2 = .088$        $\sigma = 4.728$        $F(12,178) = 1.43$  [.1542]      DW = 2.02

LM-Serial Correlation from Lags 1 to 1: F-Form(1,177) = .18 [.6735]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,174) = .59 [.6722]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,166) = .47 [.9294]

ARCH(1): F(1,176) = .11 [.7443]

ARCH(4): F(4,170) = 2.22 [.0685]

ARCH(12): F(12,154) = 1.05 [.4024]

White's Heteroscedasticity Test: F(24,153) = 1.7381 [.0245] \*

Jarque-Bera Normality Test:  $\chi^2(2) = 7.364$

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TABLE 6.3 - JAPAN

EQ(2) Modelling  $r_t$  by OLS from 1973(3) to 1988(11)

| VARIABLE                  | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|---------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                  | 8.065       | 3.438     | 3.259    | 2.346   | .032          |
| DY <sub>t</sub>           | 4.334       | 8.722     | 9.116    | .470    | .002          |
| DY <sub>t-1</sub>         | -7.311      | 12.109    | 10.326   | -.604   | .002          |
| DY <sub>t-2</sub>         | 6.373       | 12.038    | 11.974   | .529    | .002          |
| DY <sub>t-3</sub>         | -4.149      | 8.634     | 9.515    | -.481   | .001          |
| BY <sub>t</sub>           | -1.126      | 1.067     | 1.102    | -1.055  | .007          |
| BY <sub>t-1</sub>         | .189        | 1.485     | 1.311    | .127    | .000          |
| BY <sub>t-2</sub>         | -1.984      | 1.485     | 1.346    | -1.336  | .011          |
| BY <sub>t-3</sub>         | 2.414       | 1.038     | 1.085    | 2.325   | .032          |
| (MSD12r) <sub>t-1</sub>   | -.290       | .705      | .765     | -.411   | .001          |
| (MSD12r) <sub>t-2</sub>   | -.696       | .953      | 1.002    | -.730   | .003          |
| (MSD12r) <sub>t-3</sub>   | 2.077       | .949      | .970     | 2.189   | .028          |
| (MSD12r) <sub>t-4</sub>   | -1.478      | .719      | .752     | -2.055  | .025          |
| (MSD12INF) <sub>t</sub>   | .558        | 2.378     | 2.594    | .234    | .000          |
| (MSD12INF) <sub>t-1</sub> | -.996       | 5.339     | 5.604    | -.187   | .000          |
| (MSD12INF) <sub>t-2</sub> | -1.101      | 5.369     | 5.075    | -.205   | .000          |
| (MSD12INF) <sub>t-3</sub> | 1.188       | 2.397     | 2.128    | .495    | .001          |
| $r_{t-1}$                 | .170        | .143      | .137     | 1.184   | .008          |
| $r_{t-2}$                 | -.046       | .145      | .148     | -.317   | .001          |
| $r_{t-3}$                 | -.037       | .146      | .170     | -.252   | .001          |
| LOCUSM <sub>t</sub>       | -26.417     | 7.906     | 8.222    | -3.341  | .063          |
| LOCUSM <sub>t-1</sub>     | 16.036      | 10.489    | 9.714    | 1.529   | .014          |
| LOCUSM <sub>t-2</sub>     | 2.196       | 10.711    | 9.719    | .205    | .000          |
| LOCUSM <sub>t-3</sub>     | -5.631      | 8.190     | 8.231    | -.688   | .003          |

$R^2 = .227$        $\sigma = 4.495$        $F(23,165) = 2.10$  [.0040]      DW = 2.01

LM-Serial Correlation from Lags 1 to 1: F-Form(1,164) = 2.07 [.1525]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,161) = 1.08 [.3696]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,153) = .56 [.8739]

ARCH(1): F(1,163) = .21 [.6486]

ARCH(4): F(4,157) = .76 [.5560]

ARCH(12): F(12,141) = 1.28 [.2356]

White's Heteroscedasticity Test: F(38,130) = .9254 [.5973]

Jarque-Bera Normality Test:  $x^2(2) = 2.499$

TABLE 6.3 - JAPAN

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EQ(3) Modelling  $r_t$  by OLS from 1973(4) to 1988(11)

| VARIABLE                | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                | 1.948       | .516      | .498     | 3.775   | .073          |
| $\Delta Y_{t-2}$        | 3.924       | 4.369     | 4.814    | .898    | .005          |
| $\Delta BY_{t-2}$       | -2.586      | .946      | 1.021    | -2.734  | .040          |
| $(\Delta MSD12r)_{t-3}$ | 1.272       | .645      | .691     | 1.972   | .021          |
| $(MSD12INF)_t$          | -.806       | .252      | .261     | -3.205  | .054          |
| $r_{t-1}$               | .150        | .081      | .080     | 1.845   | .019          |
| $\Delta LOCUSM_t$       | -26.105     | 7.381     | 8.501    | -3.537  | .065          |
| $LOCUSM_{t-1}$          | -9.432      | 4.225     | 5.173    | -2.232  | .027          |

$R^2 = .185$        $\sigma = 4.312$        $F(7,180) = 5.85$  [.0000]       $DW = 2.03$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,179) = .32$  [.5753]  
LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,176) = .15$  [.9630]  
LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,168) = .35$  [.9787]  
ARCH(1):  $F(1,178) = .26$  [.6123]  
ARCH(4):  $F(4,172) = .51$  [.7261]  
ARCH(12):  $F(12,156) = 1.03$  [.4234]  
White's Heteroscedasticity Test:  $F(14,165) = .7760$  [.6939]  
Jarque-Bera Normality Test:  $\chi^2(2) = 7.760$

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TABLE 6.3 - JAPAN

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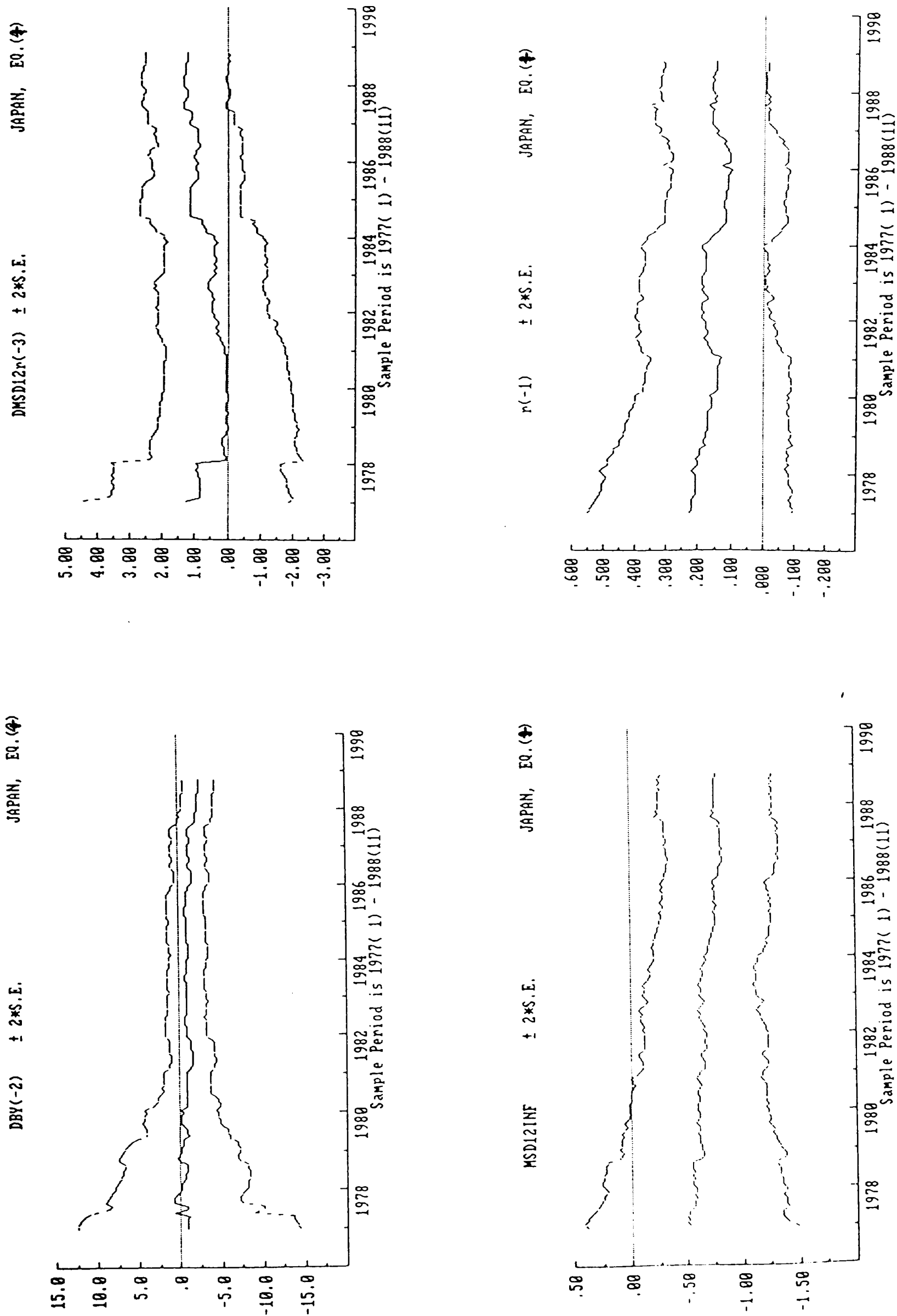
EQ(4) Modelling  $r_t$  by OLS from 1973(4) to 1988(11)

| VARIABLE                | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                | 1.895       | .512      | .493     | 3.698   | .070          |
| $\Delta BY_{t-2}$       | -2.459      | .935      | 1.006    | -2.631  | .037          |
| $(\Delta MSD12r)_{t-3}$ | 1.231       | .643      | .713     | 1.915   | .020          |
| $(MSD12INF)_t$          | -.783       | .250      | .266     | -3.132  | .051          |
| $r_{t-1}$               | .149        | .081      | .078     | 1.837   | .018          |
| $\Delta LOCUSM_t$       | -26.208     | 7.376     | 8.465    | -3.553  | .065          |
| $LOCUSM_{t-1}$          | -9.445      | 4.223     | 5.117    | -2.236  | .027          |

$R^2 = .182$        $\sigma = 4.310$        $F(6,181) = 6.70$  [.0000]       $DW = 2.03$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,180) = .25$  [.6187]  
LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,177) = .09$  [.9852]  
LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,169) = .35$  [.9783]  
ARCH(1):  $F(1,179) = .25$  [.6166]  
ARCH(4):  $F(4,173) = .65$  [.6297]  
ARCH(12):  $F(12,157) = 1.10$  [.3629]  
White's Heteroscedasticity Test:  $F(12,168) = .8719$  [.5766]  
Jarque-Bera Normality Test:  $\chi^2(2) = 7.214$

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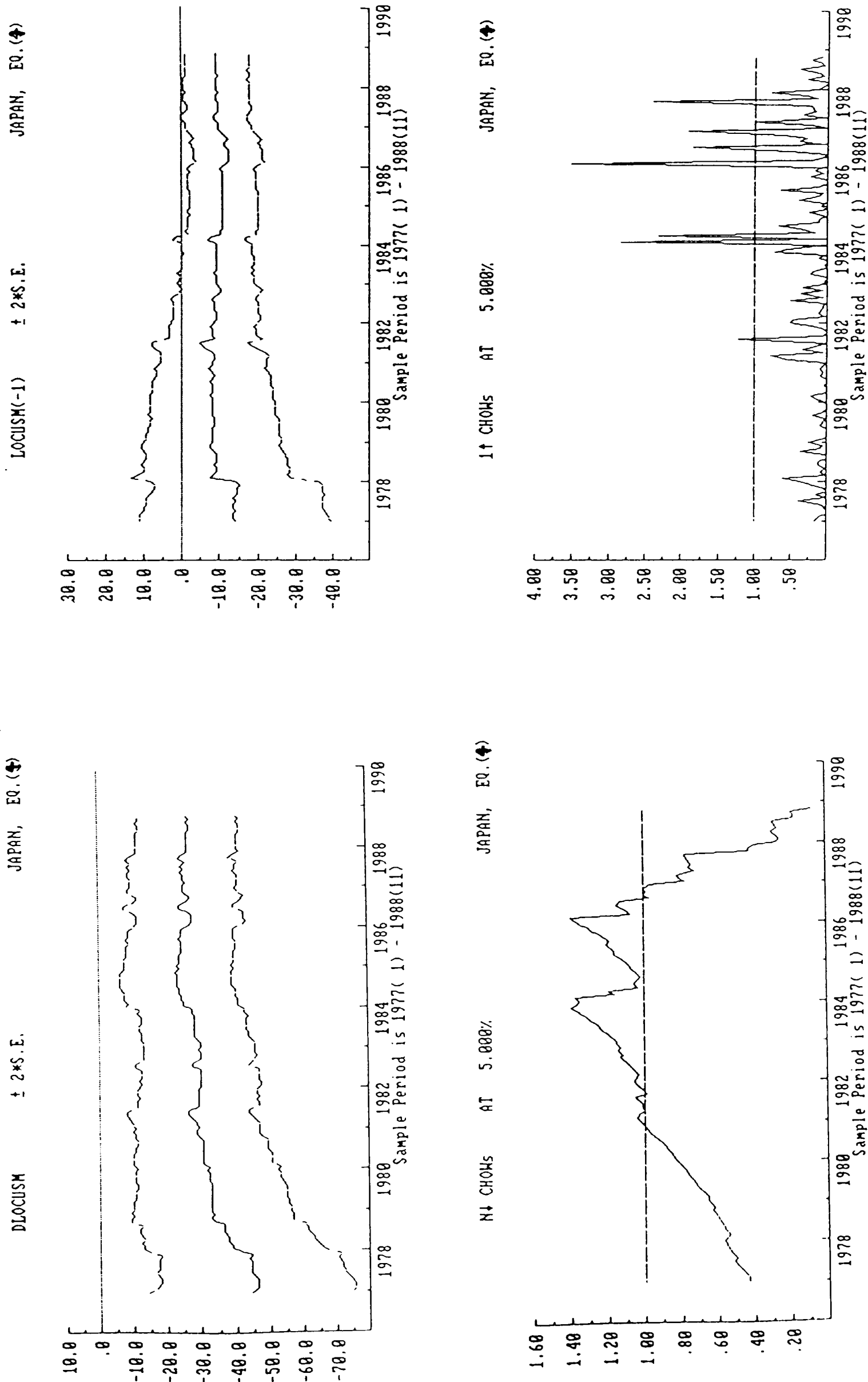


Figure 6.3

TABLE 6.3 - JAPAN

EQ(5) Modelling  $r_t$  by OLS from 1973(4) to 1988(11)

| VARIABLE                | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                | 1.941       | .496      | .436     | 3.915   | .079          |
| $\Delta Y_{t-2}$        | 4.028       | 4.152     | 4.514    | .970    | .005          |
| $\Delta BY_{t-2}$       | -1.783      | .919      | .828     | -1.939  | .021          |
| $(\Delta MSD12r)_{t-3}$ | 1.273       | .613      | .628     | 2.077   | .024          |
| $(MSD12INF)_t$          | -.815       | .240      | .245     | -3.396  | .061          |
| $r_{t-1}$               | .125        | .077      | .074     | 1.610   | .014          |
| $\Delta LOCUSM_t$       | -23.545     | 7.042     | 7.873    | -3.344  | .059          |
| $LOCUSM_{t-1}$          | -8.228      | 4.049     | 4.843    | -2.032  | .023          |
| 8603                    | 14.466      | 4.175     | .780     | 3.465   | .063          |
| 8710                    | -12.996     | 4.203     | .836     | -3.092  | .051          |

$R^2 = .273$        $\sigma = 4.097$        $F(9,178) = 7.42$  [.0000]       $DW = 1.97$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,177) = .13$  [.7174]

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,174) = .41$  [.7991]

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,166) = .38$  [.9698]

ARCH(1):  $F(1,176) = .08$  [.7829]

ARCH(4):  $F(4,170) = 1.67$  [.1596]

ARCH(12):  $F(12,154) = 1.28$  [.2373]

White's Heteroscedasticity Test:  $F(16,161) = 1.2903$  [.2090]

Jarque-Bera Normality Test:  $\chi^2(2) = 4.144$

TABLE 6.3 - JAPAN

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EQ(6) Modelling  $r_t$  by OLS from 1973(4) to 1988(11)

| VARIABLE                | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL r2 |
|-------------------------|-------------|-----------|----------|---------|------------|
| CONSTANT                | 1.677       | .486      | .457     | 3.449   | .062       |
| $\Delta Y_{t-2}$        | 4.354       | 4.093     | 4.052    | 1.064   | .006       |
| $\Delta BY_{t-2}$       | -2.724      | .886      | .803     | -3.074  | .050       |
| $(\Delta MSD12r)_{t-3}$ | 1.161       | .604      | .577     | 1.922   | .020       |
| $(MSD12INF)_t$          | -.648       | .238      | .240     | -2.726  | .040       |
| $r_{t-1}$               | .148        | .076      | .084     | 1.949   | .021       |
| $\Delta LOCUSM_t$       | -24.744     | 6.918     | 8.946    | -3.577  | .067       |
| $LOCUSM_{t-1}$          | -9.049      | 3.958     | 4.829    | -2.286  | .028       |
| $USr_t$                 | .306        | .060      | .078     | 5.122   | .128       |

$R^2 = .290$        $\sigma = 4.038$        $F(8,179) = 9.12$  [.0000]       $DW = 2.04$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,178) = .65$  [.4199]  
LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,175) = .33$  [.8594]  
LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,167) = .37$  [.9710]  
ARCH(1):  $F(1,177) = .15$  [.6963]  
ARCH(4):  $F(4,171) = .77$  [.5479]  
ARCH(12):  $F(12,155) = 1.37$  [.1872]  
White's Heteroscedasticity Test:  $F(16,162) = 1.6881$  [.0535]  
Jarque-Bera Normality Test:  $\chi^2(2) = 2.994$

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TABLE 6.3 - JAPAN

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EQ(7) Modelling  $r_t$  by OLS from 1970(1) to 1988(11)

| VARIABLE   | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------|-------------|-----------|----------|---------|---------------|
| CONSTANT   | 60.907      | 26.494    | 26.991   | 2.299   | .023          |
| TREND      | .055        | .020      | .022     | 2.699   | .032          |
| $\ln IP_t$ | -15.196     | 6.585     | 6.729    | -2.308  | .023          |

$R^2 = .038$        $\sigma = 4.904$        $F(2,224) = 4.45$  [.0127]      DW = 1.79

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EQ(8) Modelling  $r_t$  by OLS from 1973(1) to 1988(11)

| VARIABLE   | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------|-------------|-----------|----------|---------|---------------|
| CONSTANT   | 14.765      | 33.817    | 31.166   | .437    | .001          |
| TREND      | .083        | .020      | .022     | 4.154   | .084          |
| $\ln IP_t$ | -7.032      | 7.566     | 6.957    | -.929   | .005          |
| $DY_t$     | 3.591       | 1.725     | 1.943    | 2.082   | .023          |

$R^2 = .128$        $\sigma = 4.512$        $F(3,187) = 9.11$  [.0000]      DW = 1.99

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TABLE 6.3 - JAPAN

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EQ(9) Modelling  $r_t$  by OLS from 1973(4) to 1988(11)

| VARIABLE                | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                | 44.260      | 25.445    | 25.202   | 1.739   | .017          |
| $\Delta Y_{t-2}$        | 5.965       | 4.405     | 4.489    | 1.354   | .010          |
| $\Delta BY_{t-2}$       | -2.483      | .934      | 1.030    | -2.658  | .038          |
| $(\Delta MSD12r)_{t-3}$ | 1.331       | .637      | .670     | 2.091   | .024          |
| $(MSD12INF)_t$          | -.420       | .316      | .330     | -1.331  | .010          |
| $r_{t-1}$               | .097        | .083      | .073     | 1.175   | .008          |
| $\Delta LOCUSM_t$       | -24.889     | 7.320     | 7.782    | -3.400  | .061          |
| $LOCUSM_{t-1}$          | -10.200     | 4.268     | 5.196    | -2.390  | .031          |
| TREND                   | .050        | .021      | .022     | 2.390   | .031          |
| $\ln IP_t$              | -11.187     | 6.331     | 6.326    | -1.767  | .017          |

$R^2 = .216$        $\sigma = 4.254$        $F(9,178) = 5.46$  [.0000]       $DW = 2.03$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,177) = .28$  [.5948]

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,174) = .25$  [.9118]

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,166) = .62$  [.8210]

ARCH(1):  $F(1,176) = 1.05$  [.3078]

ARCH(4):  $F(4,170) = .65$  [.6304]

ARCH(12):  $F(12,154) = .79$  [.6603]

White's Heteroscedasticity Test:  $F(18,159) = 1.0670$  [.3902]

Jarque-Bera Normality Test:  $\chi^2(2) = 7.598$

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systematic drift of the Japanese index away from the US index.<sup>20</sup>

Such a simple modification is sufficient to change our whole perspective on the Japanese market. As we can see from the more parsimonious model in equation (3), what appeared to be perfect efficiency may even turn into the grossest kind of inefficiency, the ill-famed 'weak' inefficiency. The estimated coefficient on  $r_{t-1}$  is equal to .15 and, though lower than the coefficient on the 12-month moving average in the UK and the US (since returns themselves are more volatile than their moving averages), it seems to be high enough to be warranted its disquieting presence in the Japanese model. Secondly,  $LOCUSM_t$  turns out to have a preponderant effect on Japanese returns. Both the first lag of the change and the second lag of the level of this variable appear in the equation with their expected negative sign, thus underlining the strong dependence of the Japanese market on what we referred to as trend variables. This suggests that, far from showing perfect efficiency, the market is in fact dominated by trend effects, while fundamental variables seem to play only a secondary role in the determination of current returns.

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20. Notice in Table A.2 in the Appendix that, while the average real monthly return is very similar in the UK and the US over the period 1970(1)-1988(11), in Japan it is four and a half times larger than in the US. Plots of price indices in the Appendix show that, as a consequence of such extra growth, 100 real yen invested in Japan in 1970 would have become almost 700 at the end of 1988, while 100 real dollars would have just turned into 150 in the US. In the UK 100 real pounds would have done only slightly better, while it is interesting to notice that 100 real lire invested in Italy would have made a positive real return only at the end of the bull market in 1987. At the end of 1988 the real return was still negative!

In support of such a conclusion, our evidence shows that lags in fundamental variables are longer in Japan compared to the UK and the US, thus suggesting that the reaction to market fundamentals is an even slower process in Japan, which might take as long as three months to manifest itself in the market. In fact, in equation (3) return volatility appears in delta form (as in the UK), but lagged by one quarter. On the other hand, the volatility of inflation is lagged one month and is in levels (as in the US). As far as the two yields are concerned, the bond yield is also in delta form (as in the US), and lagged one quarter, while there seems to be no convenient way to incorporate a dividend yield effect in Japan. This should not come as a surprise if we look at the dividend yield graph in the Appendix. This shows that Japanese dividend yields have been steadily declining over the past fifteen years, mainly as a result of the very fast growth in the stock price level, which has outpaced growth in dividend distribution.<sup>21</sup> As a result, the dividend yield turns out to be a very bad proxy for the dividend discount rate of the Japanese

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21. Contrary to popular belief, Japanese firms do pay a fair amount of dividends. Indeed, the average dividend payout ratio (dividends as a percentage of earnings) is currently around 40 per cent. The fact that the decline in the Japanese dividend yield is mainly due to price appreciation is confirmed by the fact that the earnings-price ratio of the market exhibits the same kind of downward trend over the sample period. On the other hand, it is often suggested that Japanese accounting earnings do not accurately reflect true earnings, and are also distorted by a complex web of cross-ownerships among Japanese firms, and that computing more reliable earnings data may reduce the price-earnings ratio of the Japanese market (see French and Poterba (1989)). Finally, notice that, although clearly insignificant, the dividend yield appears in delta form and with the 'correct' sign in the Japanese equations.

market, which contains a large but unobservable expected capital gain component.

In equation (4) the delta dividend yield has been removed from the model. Notice that, contrary to what occurs in the UK and US equations, Japanese results are not affected by heteroscedasticity, and even non-normality seems to be less of a problem. In fact, once in equation (5) the usual dummies are included to remove the two most extreme returns (1986(3)=18.4% and 1987(10)=-13.5%), the Jarque-Bera test fails to reject normality. In equation (6), the current US return has been added to regressors, again with no serious consequence on the value of the coefficients of the lagged variables. On the other hand, recursive estimates of the coefficients of equation (4), presented in Figure 6.3, appear to be somewhat bumpier than their UK and the US counterparts, and the break-point tests reject stability more often.

In equations (7)-(9) we repeat the Balvers et al. ritual for the Japanese market, again obtaining the usual results. It is only worth mentioning that, in the case of Japan, the trend coefficient is strongly significant and positive over the sample period, as can perhaps be perceived by looking at the return graph in the Appendix. Nonetheless, we still believe that a trend cannot be a component of a real return generating process, and that the relationship would certainly not hold over a longer time span.<sup>22</sup> Hence we excluded a

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22. Although a long series for the Japanese index was not available, the evidence on Italian and US annual data (the latter drawn from Shiller (1989b)) indicated, unsurprisingly, the

trend from our Japanese model, despite the fact that its introduction makes the coefficients of dividend and bond yield levels, lagged one month, become strongly significant, with the correct sign.

## Italy

Finally, Table 6.4 presents results obtained on real monthly returns in the Italian market. In Italy, even the general model in equation (1) presents strong trend effects from the moving average and the delta return variables while, as in Japan, there seems to be no evidence of strong fundamental effects. Such a conclusion turned out to be confirmed as our specification search went along, thus again supporting a common sense perception about the Italian market. Despite hard trying, we found no way to account for a dividend and/or bond yield effect in Italy. While radical supporters of the EMT may be tempted to interpret this result as a proof of the efficiency of the Italian stock market, we prefer a different explanation. In our opinion, the absence of yield effects in the Italian equations simply reflects the fact that the Italian market is only tenuously related to fundamentals, and that the most important components of the return process are those related to market sentiment. Thus it is less rather

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absence of a trend in real returns. At the same time, the trend was strongly positive on monthly Italian returns from 1970, despite the fact that Italy had the worst performance over the period (see note 20) and that, as shown in Table A.2 in the Appendix, the average real monthly return on the Italian market over the period 1970(1)-1988(11) is negative.

TABLE 6.4 - ITALY

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EQ(1) Modelling  $r_t$  by OLS from 1973(1) to 1988(11)

| VARIABLE                  | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|---------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                  | 8.818       | 3.664     | 3.709    | 2.407   | .032          |
| DY <sub>t</sub>           | 3.187       | 2.730     | 2.359    | 1.168   | .008          |
| DY <sub>t-1</sub>         | -2.998      | 2.727     | 2.392    | -1.099  | .007          |
| BY <sub>t</sub>           | -.370       | 1.493     | 1.742    | -.247   | .000          |
| BY <sub>t-1</sub>         | .470        | 1.490     | 1.725    | .316    | .001          |
| (MSD12r) <sub>t-1</sub>   | -.222       | .778      | .838     | -.285   | .001          |
| (MSD12r) <sub>t-2</sub>   | -1.191      | .781      | .851     | -1.524  | .013          |
| (MSD12INF) <sub>t</sub>   | -5.457      | 3.185     | 3.172    | -1.713  | .016          |
| (MSD12INF) <sub>t-1</sub> | 4.663       | 3.225     | 3.289    | 1.446   | .012          |
| (MA12r) <sub>t-1</sub>    | -1.441      | .808      | .788     | -1.783  | .018          |
| (MA12r) <sub>t-2</sub>    | 1.966       | .824      | .819     | 2.385   | .031          |
| $\Delta r_{t-1}$          | .216        | .086      | .083     | 2.515   | .034          |
| $\Delta r_{t-2}$          | .017        | .065      | .075     | .262    | .000          |

$R^2 = .148$        $\sigma = 7.284$        $F(12,178) = 2.58$  [.0035]      DW = 2.01

LM-Serial Correlation from Lags 1 to 1: F-Form(1,177) = .01 [.9043]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,174) = .65 [.6259]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,166) = .67 [.7801]

ARCH(1): F(1,176) = .00 [.9572]

ARCH(4): F(4,170) = 1.25 [.2907]

ARCH(12): F(12,154) = 1.07 [.3872]

White's Heteroscedasticity Test: F(24,153) = 1.1539 [.2936]

Jarque-Bera Normality Test:  $\chi^2(2) = 5.548$

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TABLE 6.4 - ITALY

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EQ(2) Modelling  $r_t$  by OLS from 1973(1) to 1988(11)

| VARIABLE                 | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|--------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                 | 9.252       | 2.312     | 2.373    | 4.002   | .080          |
| (MSD12r) $_{t-1}$        | -1.146      | .307      | .307     | -3.727  | .071          |
| (MSD12INF) $_{t-1}$      | -12.716     | 5.046     | 6.032    | -2.520  | .034          |
| (MSD12INF) $_{t-2}$      | 22.410      | 9.393     | 10.583   | 2.386   | .030          |
| (MSD12INF) $_{t-3}$      | -10.757     | 5.075     | 5.273    | -2.120  | .024          |
| (MA12r) $_{t-1}$         | .406        | .197      | .259     | 2.058   | .023          |
| $\Delta r_{t-1}$         | .145        | .064      | .058     | 2.280   | .028          |
| $\Delta \text{LOCUSM}_t$ | -16.102     | 8.777     | 8.368    | -1.835  | .018          |

$R^2 = .141$        $\sigma = 7.216$        $F(7,183) = 4.28$  [.0002]      DW = 2.01

LM-Serial Correlation from Lags 1 to 1: F-Form(1,182) = .01 [.9285]  
LM-Serial Correlation from Lags 1 to 4: F-Form(4,179) = .92 [.4538]  
LM-Serial Correlation from Lags 1 to 12: F-Form(12,171) = .97 [.4816]  
ARCH(1): F(1,181) = .00 [.9688]  
ARCH(4): F(4,175) = .99 [.4153]  
ARCH(12): F(12,159) = 1.07 [.3869]  
White's Heteroscedasticity Test: F(14,168) = 1.5225 [.1076]  
Jarque-Bera Normality Test:  $\chi^2(2) = 6.519$

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TABLE 6.4 - ITALY

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EQ(3) Modelling  $r_t$  by OLS from 1973(1) to 1988(11)

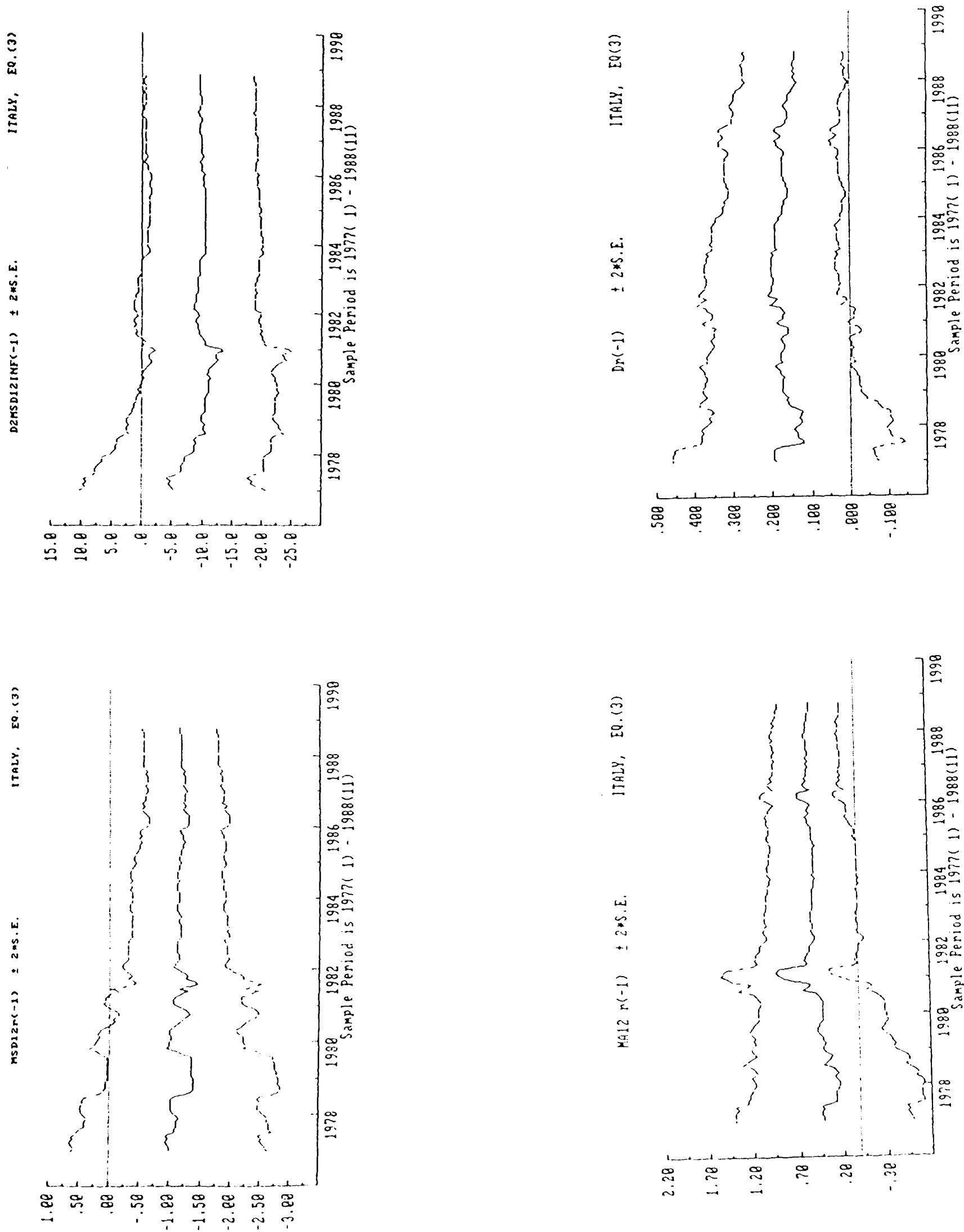
| VARIABLE                    | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-----------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                    | 7.877       | 2.142     | 2.191    | 3.678   | .068          |
| $(MSD12r)_{t-1}$            | -1.149      | .306      | .308     | -3.749  | .071          |
| $(\Delta^2 MSD12INF)_{t-1}$ | -9.513      | 4.560     | 4.668    | -2.086  | .023          |
| $(MA12r)_{t-1}$             | .525        | .179      | .229     | 2.930   | .044          |
| $\Delta r_{t-1}$            | .143        | .064      | .056     | 2.240   | .026          |
| $\Delta LOCUSM_t$           | -15.550     | 8.762     | 8.331    | -1.775  | .017          |

$R^2 = .129$        $s = 7.227$        $F(5,185) = 5.46$  [.0001]       $DW = 2.01$

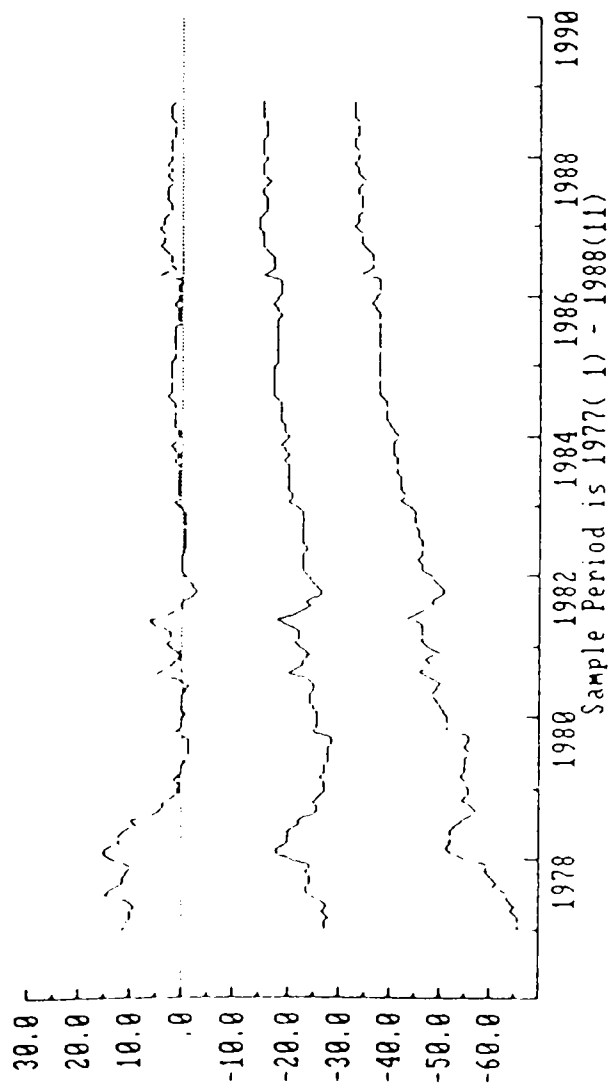
LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,184) = .01$  [.9082]  
LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,181) = .73$  [.5726]  
LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,173) = .85$  [.5973]  
ARCH(1):  $F(1,183) = .00$  [.9961]  
ARCH(4):  $F(4,177) = .93$  [.4495]  
ARCH(12):  $F(12,161) = 1.13$  [.3408]  
White's Heteroscedasticity Test:  $F(10,174) = 1.8201$  [.0602]  
Jarque-Bera Normality Test:  $\chi^2(2) = 9.310$

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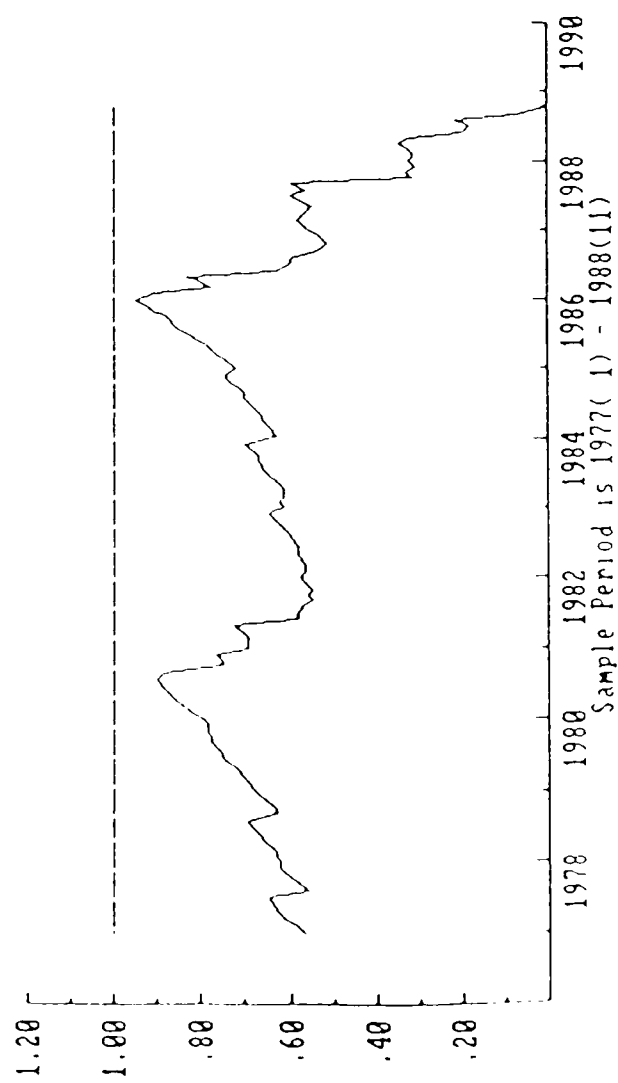
Figure 6.4



DLOCUSM      ± 2\*S.E.      ITALY, EQ.(3)



N↓ CHOWS      AT      5.000%      ITALY, EQ.(3)



1↑ CHOWS      AT      5.000%      ITALY, EQ.(3)

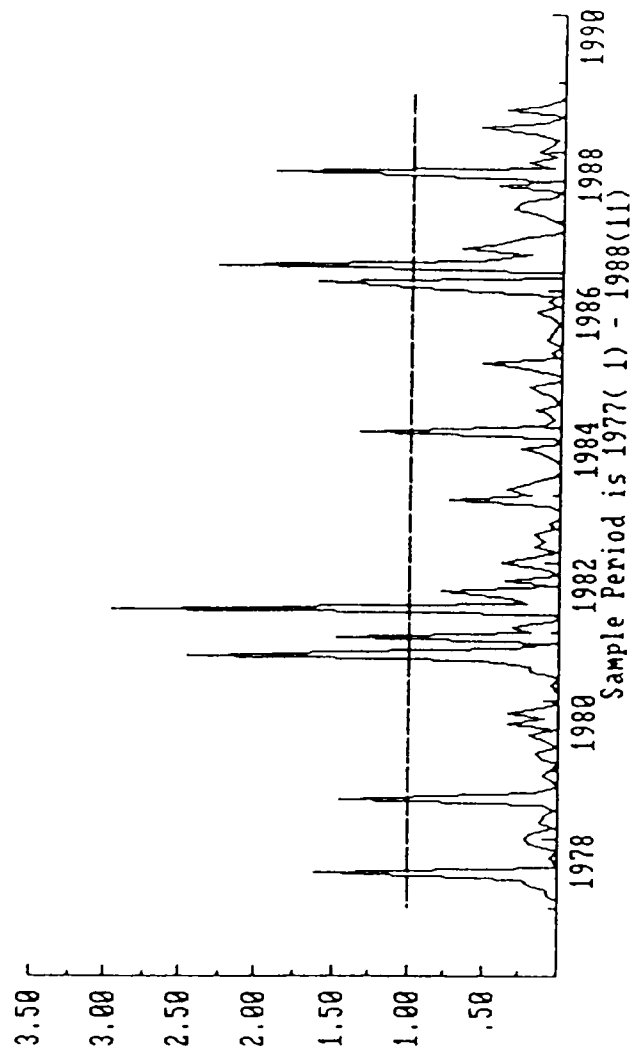


Figure 6.4

TABLE 6.4 - ITALY

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EQ(4) Modelling  $r_t$  by OLS from 1973(1) to 1988(11)

| VARIABLE                        | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|---------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                        | 7.269       | 2.062     | 2.093    | 3.526   | .064          |
| (MSD12r) $_{t-1}$               | -1.056      | .295      | .293     | -3.583  | .066          |
| ( $\Delta^2$ MSD12INF) $_{t-1}$ | -10.134     | 4.375     | 4.257    | -2.316  | .029          |
| (MA12r) $_{t-1}$                | .555        | .176      | .202     | 3.149   | .051          |
| $\Delta r_{t-1}$                | .122        | .061      | .052     | 1.990   | .021          |
| $\Delta$ LOCUSM $_t$            | -15.072     | 8.397     | 8.087    | -1.795  | .017          |
| 8106                            | -23.336     | 7.062     | 1.611    | -3.304  | .056          |
| 8603                            | 18.870      | 7.089     | 1.703    | 2.662   | .037          |

$R^2 = .208$        $\sigma = 6.926$        $F(7,183) = 6.88$  [.0000]      DW = 2.08

LM-Serial Correlation from Lags 1 to 1: F-Form(1,182) = .80 [.3720]  
LM-Serial Correlation from Lags 1 to 4: F-Form(4,179) = 1.29 [.2743]  
LM-Serial Correlation from Lags 1 to 12: F-Form(12,171) = .66 [.7912]  
ARCH(1): F(1,181) = .00 [.9458]  
ARCH(4): F(4,175) = .02 [.9988]  
ARCH(12): F(12,159) = .41 [.9595]  
White's Heteroscedasticity Test: F(12,170) = .7185 [.7185]  
Jarque-Bera Normality Test:  $\chi^2(2) = 6.534$

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TABLE 6.4 - ITALY

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EQ(5) Modelling  $r_t$  by OLS from 1973(1) to 1988(11)

| VARIABLE                    | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-----------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                    | 7.347       | 2.089     | 2.095    | 3.518   | .063          |
| $(MSD12r)_{t-1}$            | -1.076      | .299      | .294     | -3.602  | .066          |
| $(\Delta^2 MSD12INF)_{t-1}$ | -9.095      | 4.437     | 4.352    | -2.050  | .022          |
| $(MA12r)_{t-1}$             | .495        | .174      | .225     | 2.838   | .042          |
| $\Delta r_{t-1}$            | .134        | .062      | .057     | 2.167   | .025          |
| $\Delta LOCUSM_t$           | -15.029     | 8.523     | 8.625    | -1.763  | .017          |
| $USr_t$                     | .349        | .103      | .112     | 3.405   | .059          |

$R^2 = .180$        $\sigma = 7.029$        $F(6,184) = 6.74$  [.0000]       $DW = 2.03$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,183) = .19$  [.6658]  
LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,180) = 1.30$  [.2700]  
LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,172)=1.17$  [.3089]  
ARCH(1):  $F(1,182) = .23$  [.6302]  
ARCH(4):  $F(4,176) = .91$  [.4603]  
ARCH(12):  $F(12,159) = 1.47$  [.1405]  
White's Heteroscedasticity Test:  $F(12,171) = .6380$  [.0852]  
Jarque-Bera Normality Test:  $\chi^2(2) = 11.951$

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TABLE 6.4 - ITALY

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| EQ(6) Modelling $r_t$ by OLS from 1972(1) to 1988(11)               |             |           |          |         |               |
|---------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| VARIABLE                                                            | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
| CONSTANT                                                            | 35.654      | 41.433    | 38.243   | .861    | .004          |
| TREND                                                               | .030        | .017      | .017     | 1.715   | .015          |
| $\ln IP_t$                                                          | -8.650      | 9.523     | 8.838    | -.908   | .004          |
| $R^2 = .020$ $\sigma = 7.432$ $F(2,200) = 2.09$ [.1265] $DW = 1.76$ |             |           |          |         |               |

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| EQ(7) Modelling $r_t$ by OLS from 1973(1) to 1988(11)               |             |           |          |         |               |
|---------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| VARIABLE                                                            | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
| CONSTANT                                                            | 28.517      | 45.299    | 42.291   | .630    | .002          |
| TREND                                                               | .034        | .019      | .019     | 1.851   | .018          |
| $\ln IP_t$                                                          | -7.552      | 10.369    | 9.748    | -.728   | .003          |
| $DY_t$                                                              | .545        | .497      | .528     | 1.096   | .006          |
| $R^2 = .028$ $\sigma = 7.594$ $F(3,187) = 1.77$ [.1553] $DW = 1.75$ |             |           |          |         |               |

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TABLE 6.4 - ITALY

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EQ(8) Modelling  $r_t$  by OLS from 1973(1) to 1988(11)

| VARIABLE                    | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-----------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                    | 18.431      | 43.785    | 40.228   | .421    | .001          |
| $(MSD12r)_{t-1}$            | -1.129      | .310      | .310     | -3.639  | .068          |
| $(\Delta^2 MSD12INF)_{t-1}$ | -9.404      | 4.571     | 4.748    | -2.057  | .023          |
| $(MA12r)_{t-1}$             | .454        | .191      | .243     | 2.232   | .027          |
| $\Delta r_{t-1}$            | .142        | .064      | .056     | 2.232   | .027          |
| $\Delta LOCUSM_t$           | -15.446     | 8.774     | 8.387    | -1.760  | .017          |
| TREND                       | .016        | .017      | .018     | .940    | .005          |
| $\ln IP_t$                  | -2.817      | 10.061    | 9.259    | -.280   | .000          |

$R^2 = .136$        $\sigma = 7.235$        $F(7,183) = 4.12$  [.0003]       $DW = 2.02$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,182) = .04$  [.8445]

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,179) = .79$  [.5361]

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,171) = .88$  [.5688]

ARCH(1):  $F(1,181) = .00$  [.9583]

ARCH(4):  $F(4,175) = 1.28$  [.2796]

ARCH(12):  $F(12,159) = 1.28$  [.2321]

White's Heteroscedasticity Test:  $F(14,168) = 1.4983$  [.1163]

Jarque-Bera Normality Test:  $\chi^2(2) = 8.015$

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than more fundamental efficiency which explains the insignificance of yield variables in Italy, and confusion between Chaos and Cosmos should be left to metaphysical fantasies.

In equation (2) the second lags of the moving average and the delta return have been removed, along with dividend and bond yields and the second lag of the return volatility. In addition, as in Japan, the delta of  $LOCUSM_t$  - the deviation of the log ratio between the Italian and the US indices from its 12-month moving average - has been included in the equation, and appears with its expected negative sign, while, unlike Japan, there is no evidence of a level effect in  $LOCUSM_t$ .<sup>23</sup> Other relevant differences between the Japanese and the Italian models include the presence of a moving average plus delta return effect in Italy, which in this respect mirrors the UK and US results, and the absence of a bond yield as well as a dividend yield effect. In addition, the volatility of returns has a clear negative coefficient in the Italian model. As explained in the previous section, this suggests that it is impossible for risk takers to benefit from volatility in the Italian market - a result which may be interpreted as evidence that the average Italian investor is not risk averse. As far as inflation volatility is concerned, while equation (1) seems to suggest the presence of a first-lag delta effect (as in

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23. Unlike Japan, the drift away from the US market has been negative in Italy, as reflected by the fact that  $LOCUSM_t$  has a negative mean over the period. Also, among the four markets examined, Italy has by far the most volatile returns, showing the highest standard deviation and the lowest mean-variance ratio.

the UK), unrestricted estimation including further lags revealed that a better way to incorporate such a variable in the Italian model is in a double delta form (i.e. the first difference of the first difference), lagged two months. Notice, in fact, that in equation (2) the coefficients of  $MSD12INF_{t-1}$  and  $MSD12INF_{t-3}$  have the same negative sign and similar magnitudes, while the coefficient of  $MSD12INF_{t-2}$  has a positive sign and is roughly twice as large in absolute terms. This is exactly what we would find if the double delta of  $MSD12INF_{t-1}$  had a negative effect on current returns. Such a restriction is actually implemented in equation (3), and it is not rejected by the data. In addition, the restricted equation allows for a higher coefficient on the moving average term. Combined with the evidence from the other markets, this result suggests the existence of a positive relation between the amount of differencing required to establish the presence of a negative effect of inflation volatility on current returns and the average level of inflation in each country over the sample period (see Table A.2 in the Appendix).

As in the case of Japan, the Italian equations pass the heteroscedasticity tests, and the Jarque-Bera test is very close to rejecting non-normality at the 5% level. As usual, in equation (4) the two extreme opposite returns<sup>24</sup> (1981(6)=-20.9% and 1986(3)=23.7%) have been taken out of the data set, thus improving homoscedasticity

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24. Notice that Italy is the only market in which the largest negative return does not coincide with the October 1987 crash.

and normality, while in equation (5) the current real return in the US is added to regressors, and has again no major consequence on the other coefficients.

As far as the recursive coefficients of equation (3) are concerned, Figure 6.4 shows that they are rather bumpy, although somewhat less than in Japan. The most significant jump occurs in the 1980-81 mini-boom, which was followed by a sudden crash in 1981(6). Finally, equations (6)-(8) reject Balvers et al.'s model, thus confirming results shown on annual data in Chapter 4.

### III. Conclusions.

Blinded by their a priori beliefs about efficiency, generations of financial economists have been accustomed to calling off the trial of the EMT as soon as the suspect, asked whether she<sup>25</sup> killed the victim, uttered a candid 'No'. We think we have shown in this study

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25. Italian students writing in English are sooner or later faced with the He-or-She conundrum which, due to a different syntax of pronouns, is less of a nuisance in the Italian language. With time, we even learn to associate different characters with different ways of dealing with the problem. So, for instance, the neat and conscientious scholar will cope with propositions like: "He or she will choose his or her commodity bundles according to his or her preferences" only to demonstrate his (or her!) earnest support for sex parity. The 'alternative' male academician, on the other hand, will feel seductively original using only 'she' and 'her', while the tedious chap will opt for a strict use of an equitable 'it'. In the course of this study we chose to ignore the problem rather than try to come up with our own fancy-silly way to solve it. Although this is probably the most reasonable way to deal with it (indeed very sensibly followed by most women-scholars), we like, in the end, to elaborate on the cliché of Italian 'macho-ism' and use 'she' to address what we have been chasing all along in this study - the EMT. We may mention (but it is only a feeble excuse) that the Italian word for Theory (Teoria) has a feminine gender.

that, once this peculiar procedure is inverted, little effort and imagination are actually required to convict the EMT. However, although our results are probably sufficient to reject the efficiency view, our equations are clearly not intended to be exhaustive representations of the return generating process. The only purpose of this work has been to show that, however randomly fluctuating stock prices may appear to our indolent minds, the return process is far from anything like a martingale difference, since past information does contribute, if only partially, to explain variations in current returns.

The inversion of the trial procedure based on orthogonality tests makes the uncovering of potential return predictors a potentially endless job. Indeed, once a breach in the orthogonality bulwark has been opened, it is always tempting to delay conclusions and look for further evidence. Like the investigator who tricked the suspect into confession, we can hardly be content with a simple 'Yes', as we would like to know much more about the events. But the trial has to come to an end, and the investigator should leave the courtroom with a relieving sense of accomplishment, even though he will later go back to the evidence and find out in more detail. Hence a conclusion to the present study must come with the decision to put a temporary halt to the search for significant relationships between current returns and past information. Of course, this does not mean that results cannot be improved upon. On the contrary, we believe

that our equations represent only a limited instance of what can be achieved in the future with more research and more effort.

Professor Kendall's well-known 1953 paper is at the origin of the random walk literature on stock market behaviour. Kendall, who wrote the paper after an unsuccessful attempt to extract systematic components from the time series of stock and other speculative prices, was the first to suggest that the failure might be due to the fact that the price process is close to a random walk. However, it would be wrong to regard this very interesting paper as a mere harbinger of the random walk theory. In fact, although Kendall argued that the weak serial correlation found in price first differences would overrule any attempt to use price series for predictive purposes, he carefully remarked that "... the observed serials, small as they are, [may] have some significance. But evidently the systematic element is slight compared with the random component and a very precise technique is going to be necessary in order to extract it, unless we know what to look for" (p.17). This is exactly what we have done in this work, on the basis of a simple representation of the stock market game emphasising the conventional nature of the process of stock price determination.

In 1948 the American sociologist R.K. Merton wrote a paper titled 'The Self-Fulfilling Prophecy', in which he gave several examples of circumstances in which "If men define situations as real, they are real in their consequences". Merton called this the 'Thomas

Theorem', after his fellow sociologist W.I. Thomas, who dedicated several works to the study of this phenomenon, but he carefully reminded us that essentially the same proposition had been set forth by many others before Thomas, including Bishop Bossuet, Mandeville, Marx, Freud and Sumner. We like to conclude our study by adding to this list the Italian writer Alessandro Manzoni who, in a passage of *I Promessi Sposi* (*The Betrothed*, 1827), describes the plague and famine which stroke Milan in the first half of the seventeenth century, and tells us how hungry mobs used to assault bakeries all over town and steal the bread hoarded by unscrupulous bakers in expectation of higher prices. One of these assaults developed after somebody spread the rumour that another bakery was about to be sacked. As a result, a large crowd gathered outside the bakery and, although the rumour was in fact false, an assault immediately took place. Commenting on this episode, Manzoni wrote the sentence we have used as the epigraph of our study, which reads: "Often in such circumstances, the announcement of something makes it come true".

**APPENDICES**

## A.1

We present here unit root and cointegration tests on dividend and bond yields for the UK and US stock markets. The reported results should however be interpreted very cautiously, as the tests are run over a relatively short time span of less than twenty years. Although the frequency of the data is monthly, it is well-known that the power of the tests is more closely related to the length of the sample period than to the number of observations.<sup>1</sup>

Equations (A.1) and (A.2) in Table A.1 report Augmented Dickey-Fuller tests on the UK dividend and bond yields. Three lags in the delta dividend yield and two lags in the delta bond yields had to be added to regressors in order to obtain white noise residuals. Keeping the above proviso in mind, we conclude that both tests cannot reject the null of non stationarity at the 5% level.<sup>2</sup> The Durbin-Watson tests of the regressions of  $DY_t$  and  $BY_t$  on a constant and their own first lag give the same indication.

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1. See Shiller and Perron (1985).

2. Notice that, although the constant is significant in equations (A1) and (A2), it becomes insignificant when the equations are estimated under the null of a unit root. This rules out using the ordinary t-statistic critical values to test the null. The same is true for all other ADF equations in the Table.

The cointegrating regression between  $DY_t$  and  $BY_t$  is presented in equation (A.3). The Durbin-Watson coefficient is very close to the critical value necessary to reject the null of non stationarity at the 5% level. In addition, in equation (A4) the Dickey-Fuller test on the cointegrating regression residuals suggests a strong rejection of non stationarity.<sup>3</sup> Hence both tests point towards detecting cointegration between the UK dividend and bond yields, thereby justifying their presence in level form in the UK equations. In this respect, notice that the coefficient of  $BY_t$  in the cointegrating regression is equal to .52, which is close to the ratio of the coefficients of  $BY_t$  and  $DY_t$  in equation (5), Table 6.1, equal to .46. The two should indeed be equal if  $BY_t$  and  $DY_t$  are cointegrated.

Equations (A1-A4) in Table A.2 repeat the same tests for the US dividend and bond yields. Equations (A1) and (A2) test the null of non stationarity for the two series. Notice that, while no lag of the dependent variable is necessary for the dividend yield equation, up to five lags had to be added to the bond yield equation to obtain white noise residuals.<sup>4</sup> As in the UK, in both series the ADF test cannot reject the null of non stationarity, a result which is also suggested by the Durbin-Watson tests.

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3. Although three lags of the residuals must be added to regressors to eliminate autocorrelation in the equation residuals, results are the same with fewer or no lags.

4. Test results are the same with fewer or no lags.

Equation (A3) contains the cointegrating regression between of  $DY_t$  on  $BY_t$ . Here the Durbin-Watson coefficient is significantly lower compared to the UK, and far below the critical value. This result is consistent with the ADF test on the cointegrating regression residuals (equation (A.4)), which also suggests that the two series are not cointegrated in the US. This justifies their appearance in delta form in the US equations in Table 6.2.

TABLE A.1 - UNITED KINGDOM

Augmented Dickey-Fuller Test for Unit Roots in  $DY_t$ .

EQ(A1) Modelling  $\Delta DY_t$  by OLS from 1970(5) to 1988(12)

| VARIABLE          | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT          | .388        | .132      | .310     | 2.938   | .038          |
| TREND             | -.000       | .000      | .000     | -.475   | .001          |
| $DY_{t-1}$        | -.072       | .022      | .068     | -3.236  | .046          |
| $\Delta DY_{t-1}$ | .269        | .066      | .135     | 4.096   | .072          |
| $\Delta DY_{t-2}$ | -.171       | .066      | .166     | -2.580  | .030          |
| $\Delta DY_{t-3}$ | .219        | .066      | .106     | 3.345   | .049          |

$R^2 = .133$        $\sigma = .430$        $F(5,218) = 6.69$  [.0000]       $DW = 1.95$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,217) = 2.29$  [.1314]

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,214) = 1.00$  [.4068]

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,206) = .63$  [.8189]

DURBIN-WATSON TEST:  $DW(DY_t) = .11$

TABLE A.1 - UNITED KINGDOM

Augmented Dickey-Fuller Test for Unit Roots in  $BY_t$ .

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EQ(A2) Modelling  $\Delta BY_t$  by OLS from 1970(4) to 1988(12)

| VARIABLE          | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT          | .377        | .166      | .150     | 2.269   | .023          |
| TREND             | -.001       | .000      | .000     | -1.289  | .008          |
| $BY_{t-1}$        | -.026       | .013      | .014     | -2.044  | .019          |
| $\Delta BY_{t-1}$ | .389        | .066      | .074     | 5.918   | .137          |
| $\Delta BY_{t-2}$ | -.165       | .066      | .071     | -2.496  | .028          |

$R^2 = .158$        $\sigma = .423$        $F(4,220) = 10.32$  [.0000]       $DW = 2.03$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,219) = 1.55$  [.2141]  
 LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,216) = .63$  [.6381]  
 LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,213) = .45$  [.8715]

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DURBIN-WATSON TEST:  $DW(BY_t) = .04$

TABLE A.1 - UNITED KINGDOM

Cointegrating regression of dividend and bond yields.

EQ(A3) Modelling  $DY_t$  by OLS from 1970(1) to 1988(12)

| VARIABLE                                                                                 | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|------------------------------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                                                                                 | -1.019      | .255      | .387     | -3.994  | .066          |
| $BY_t$                                                                                   | .520        | .021      | .036     | 24.206  | .722          |
| <hr/>                                                                                    |             |           |          |         |               |
| $R^2 = .722 \quad \sigma = .722 \quad F(1,226) = 585.95 \text{ [.0000]} \quad DW = .345$ |             |           |          |         |               |

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ADF Test for Unit Roots in the cointegrating regression residuals.

EQ(A4) Modelling  $\Delta cr_t$  by OLS from 1970(5) to 1988(12)

| VARIABLE                                                                               | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|----------------------------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                                                                               | -.013       | .054      | .060     | -.243   | .000          |
| TREND                                                                                  | .000        | .000      | .000     | .211    | .000          |
| $cr_{t-1}$                                                                             | -.219       | .041      | .135     | -5.284  | .114          |
| $\Delta cr_{t-1}$                                                                      | .186        | .067      | .143     | 2.775   | .034          |
| $\Delta cr_{t-2}$                                                                      | -.095       | .065      | .163     | -1.461  | .010          |
| $\Delta cr_{t-3}$                                                                      | .268        | .065      | .117     | 4.138   | .073          |
| <hr/>                                                                                  |             |           |          |         |               |
| $R^2 = .177 \quad \sigma = .389 \quad F(5,218) = 9.35 \text{ [.0000]} \quad DW = 2.00$ |             |           |          |         |               |

LM-Serial Correlation from Lags 1 to 1: F-Form(1,217) = .00 [.9527]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,214) = 1.12 [.3472]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,206) = .78 [.6692]

TABLE A.2 - UNITED STATES

Augmented Dickey-Fuller Test for Unit Roots in  $DY_t$ .

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| EQ(A1) Modelling $\Delta DY_t$ by OLS from 1970(2) to 1988(12)                  |             |           |          |         |               |
|---------------------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| VARIABLE                                                                        | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
| CONSTANT                                                                        | .112        | .067      | .068     | 1.666   | .012          |
| TREND                                                                           | -.000       | .000      | .000     | -.241   | .000          |
| $DY_{t-1}$                                                                      | -.025       | .015      | .019     | -1.626  | .012          |
| $R^2 = .013$ $\sigma = .212$ $F(2,224) = 1.47$ [.2318] $DW = 1.83$              |             |           |          |         |               |
| LM-Serial Correlation from Lags 1 to 1: $F\text{-Form}(1,223) = 1.73$ [.1900]   |             |           |          |         |               |
| LM-Serial Correlation from Lags 1 to 4: $F\text{-Form}(4,220) = .66$ [.6209]    |             |           |          |         |               |
| LM-Serial Correlation from Lags 1 to 12: $F\text{-Form}(12,212) = 1.00$ [.4500] |             |           |          |         |               |
| <hr/>                                                                           |             |           |          |         |               |
| DURBIN-WATSON TEST: $DW(DY_t) = .05$                                            |             |           |          |         |               |

TABLE A.2 - UNITED STATES

Augmented Dickey-Fuller Test for Unit Roots in  $BY_t$ .

EQ(A2) Modelling  $\Delta BY_t$  by OLS from 1970(7) to 1988(12)

| VARIABLE          | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|-------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT          | .164        | .093      | .116     | 1.771   | .014          |
| TREND             | -.001       | .000      | .000     | .636    | .002          |
| $BY_{t-1}$        | -.021       | .012      | .017     | -1.737  | .014          |
| $\Delta BY_{t-1}$ | .444        | .067      | .100     | 6.623   | .170          |
| $\Delta BY_{t-2}$ | -.295       | .073      | .101     | -4.040  | .071          |
| $\Delta BY_{t-3}$ | .147        | .075      | .095     | 1.954   | .018          |
| $\Delta BY_{t-4}$ | -.095       | .073      | .109     | -1.300  | .008          |
| $\Delta BY_{t-5}$ | .189        | .067      | .098     | 2.811   | .036          |

$R^2 = .208$        $\sigma = .331$        $F(7,214) = 8.05$  [.0000]       $DW = 1.95$

LM-Serial Correlation from Lags 1 to 1:  $F\text{-Form}(1,213) = 3.62$  [.0583]

LM-Serial Correlation from Lags 1 to 4:  $F\text{-Form}(4,210) = 1.51$  [.1994]

LM-Serial Correlation from Lags 1 to 12:  $F\text{-Form}(12,202)=1.45$  [.1471]

DURBIN-WATSON TEST:  $DW(BY_t) = .02$

TABLE A.2 - UNITED STATES

Cointegrating regression of dividend and bond yields.

EQ(A3) Modelling  $DY_t$  by OLS from 1970(1) to 1988(12)

| VARIABLE                                                             | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|----------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                                                             | 1.769       | .185      | .147     | 9.573   | .289          |
| $BY_t$                                                               | .270        | .020      | .015     | 13.763  | .456          |
| $R^2 = .456$ $\sigma = .688$ $F(1,226) = 189.42$ [.0000] $DW = .087$ |             |           |          |         |               |

=====

ADF Test for Unit Roots in the cointegrating regression residuals.

EQ(A4) Modelling  $\Delta cr_t$  by OLS from 1970(2) to 1988(12)

| VARIABLE                                                           | COEFFICIENT | STD ERROR | H.C.S.E. | t-VALUE | PARTIAL $r^2$ |
|--------------------------------------------------------------------|-------------|-----------|----------|---------|---------------|
| CONSTANT                                                           | .018        | .028      | .022     | .646    | .002          |
| TREND                                                              | -.000       | .000      | .000     | -.858   | .003          |
| $cr_{t-1}$                                                         | -.047       | .020      | .025     | -2.323  | .024          |
| $R^2 = .024$ $\sigma = .201$ $F(2,224) = 2.72$ [.0679] $DW = 1.98$ |             |           |          |         |               |

LM-Serial Correlation from Lags 1 to 1: F-Form(1,223) = .01 [.9133]

LM-Serial Correlation from Lags 1 to 4: F-Form(4,220) = .77 [.5471]

LM-Serial Correlation from Lags 1 to 12: F-Form(12,212) = .69 [.7649]

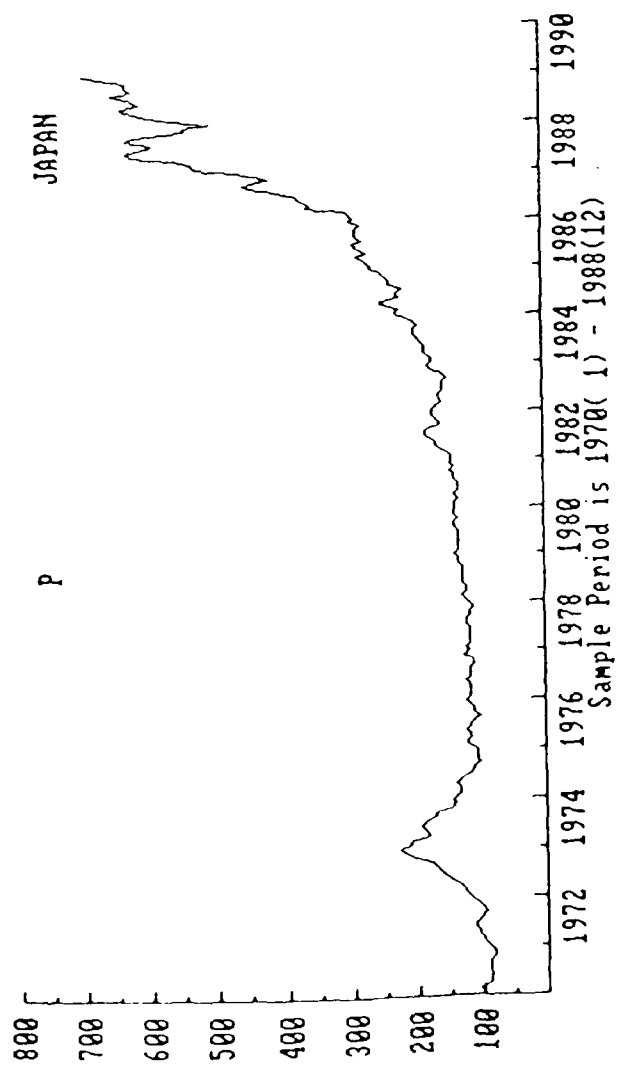
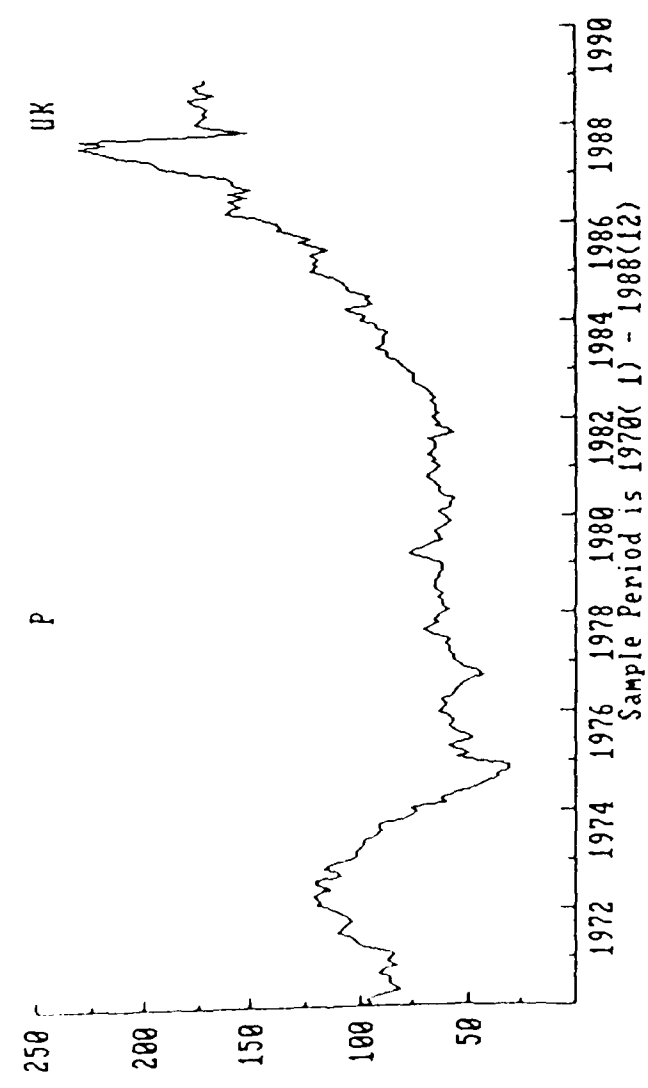
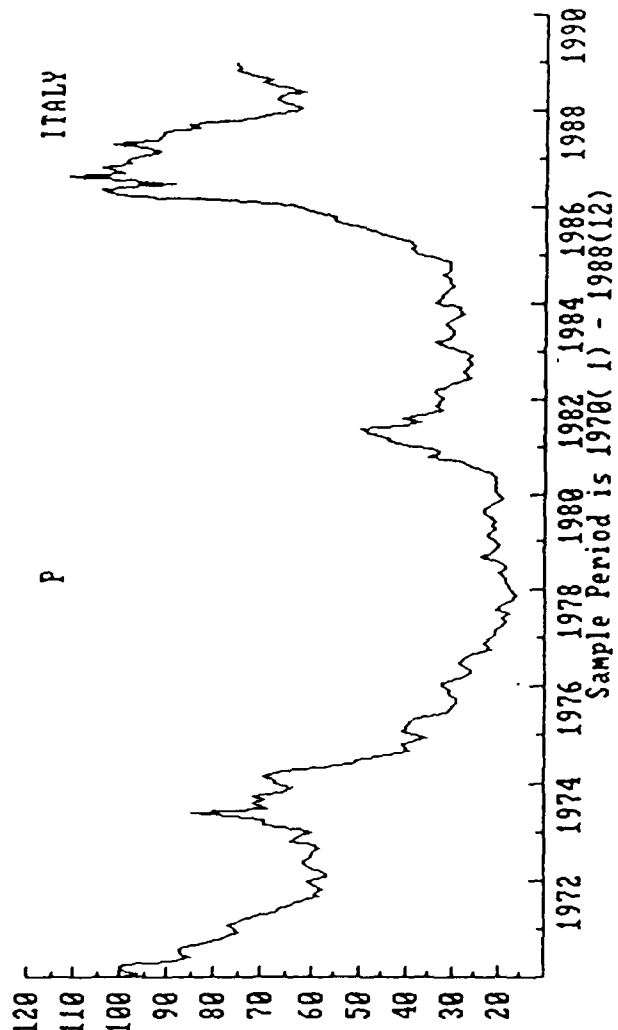
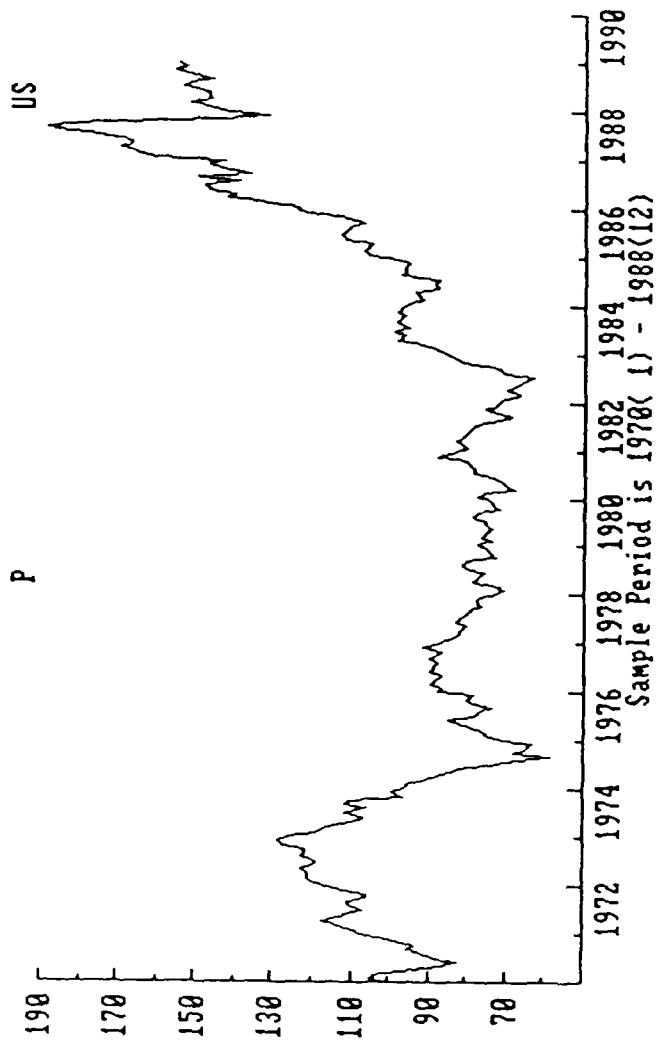
A.2

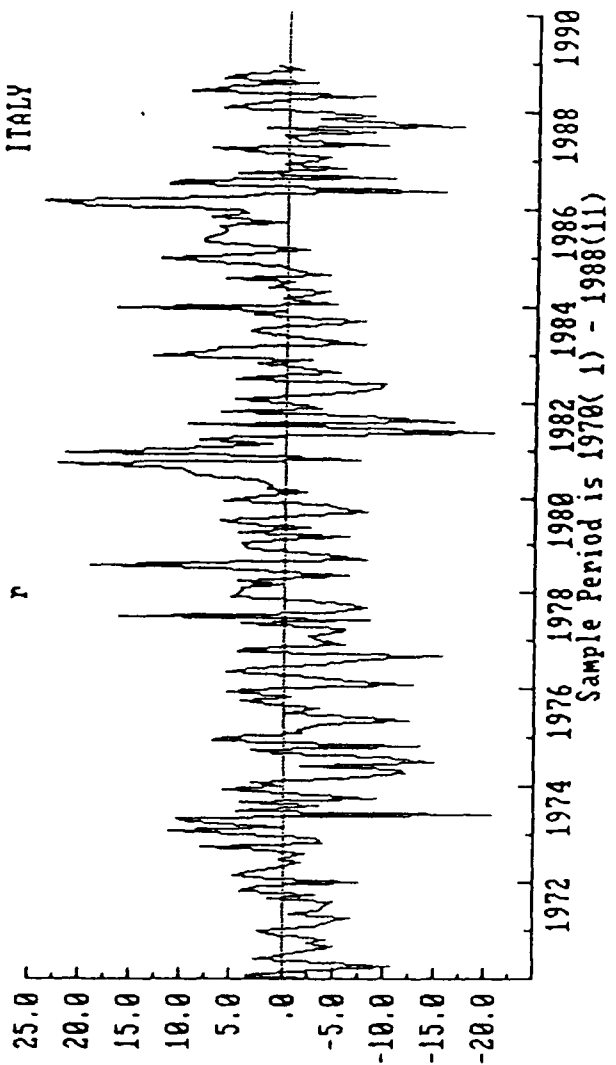
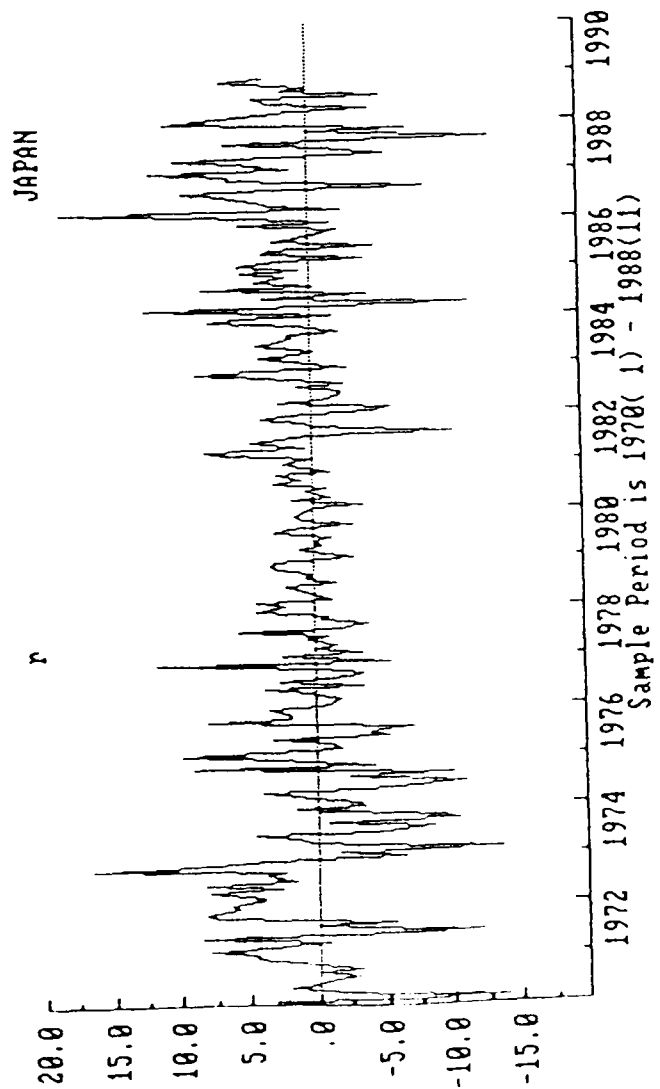
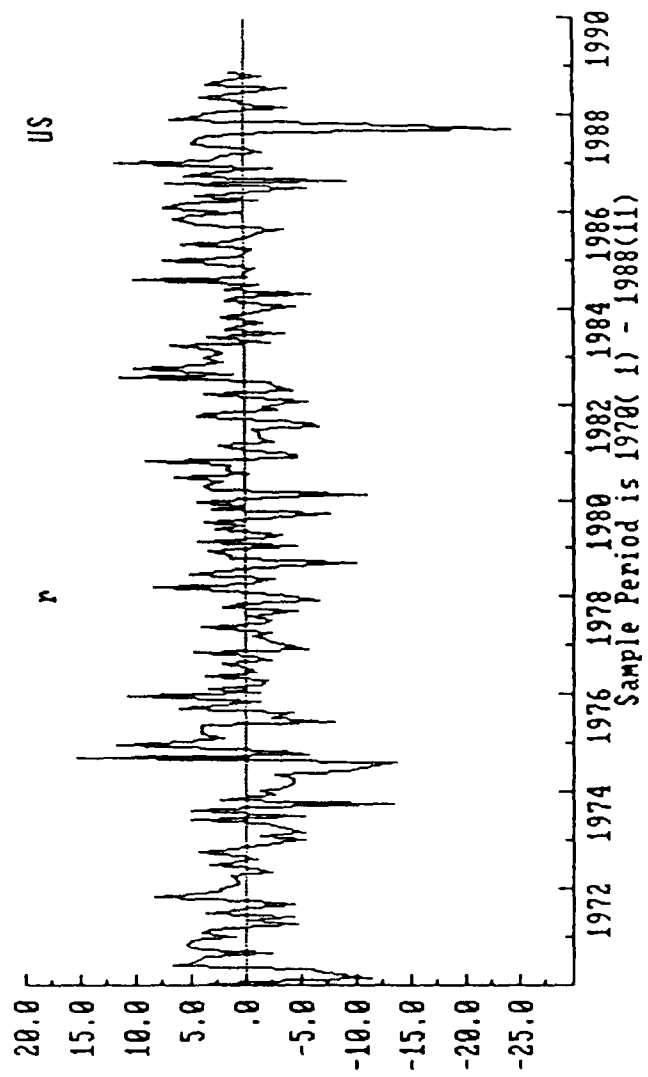
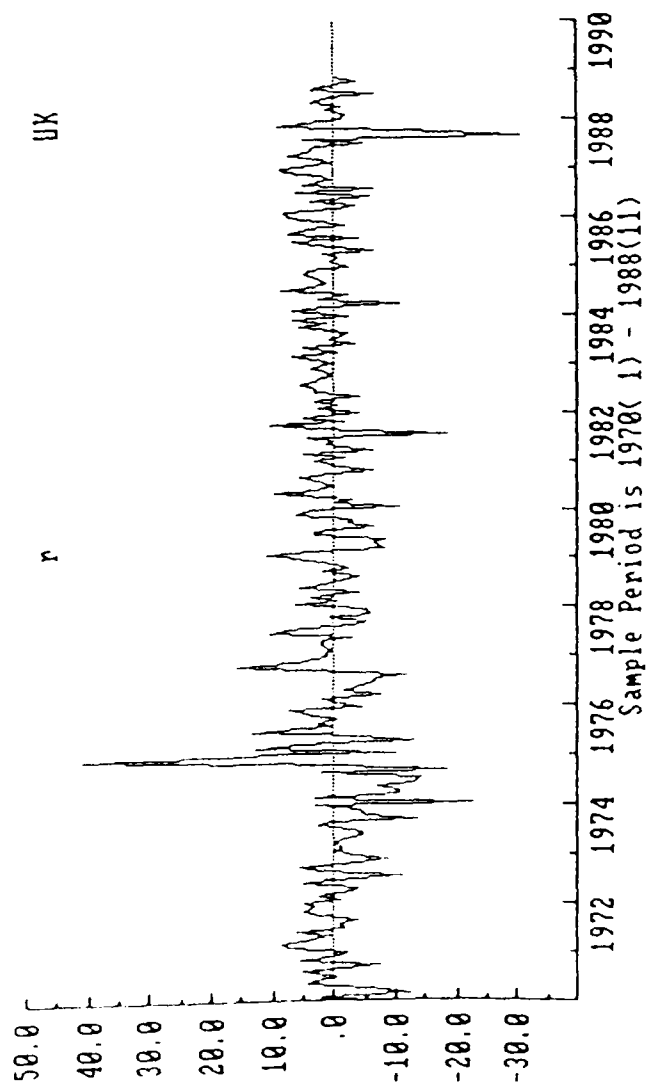
TABLE A.3

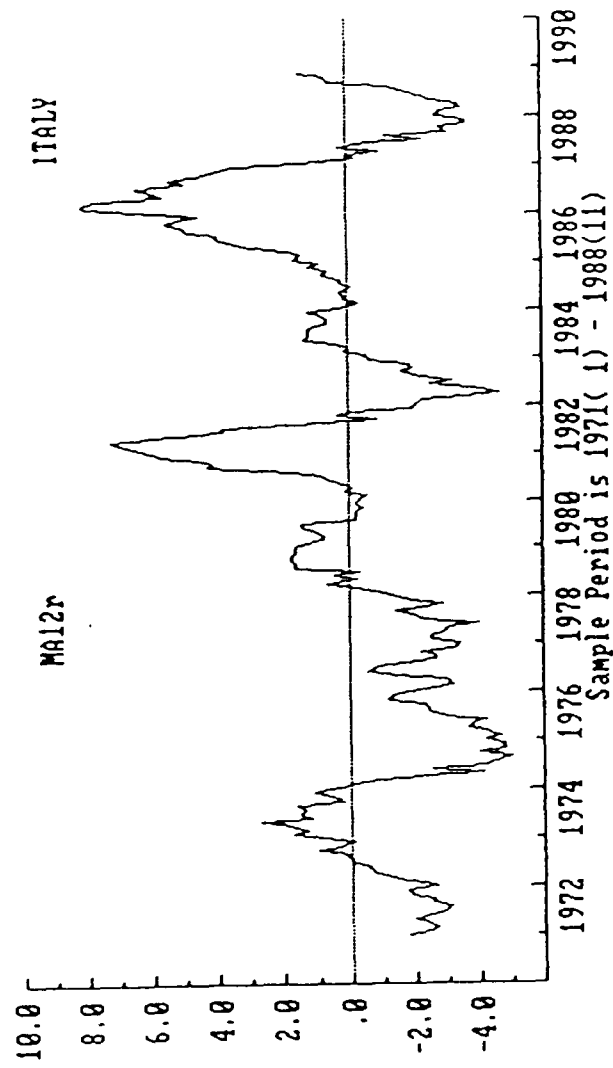
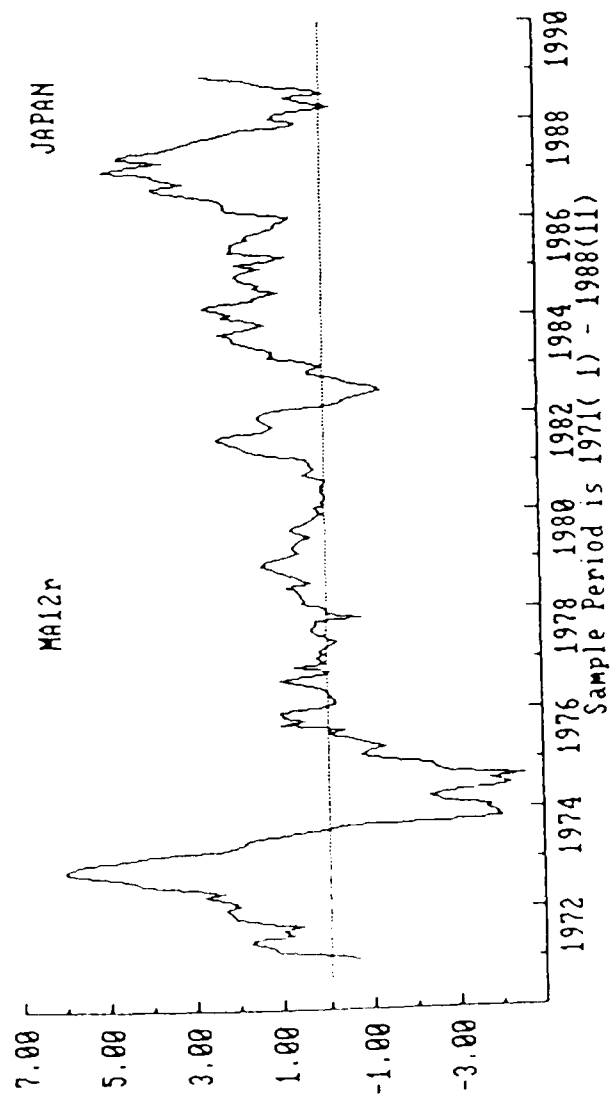
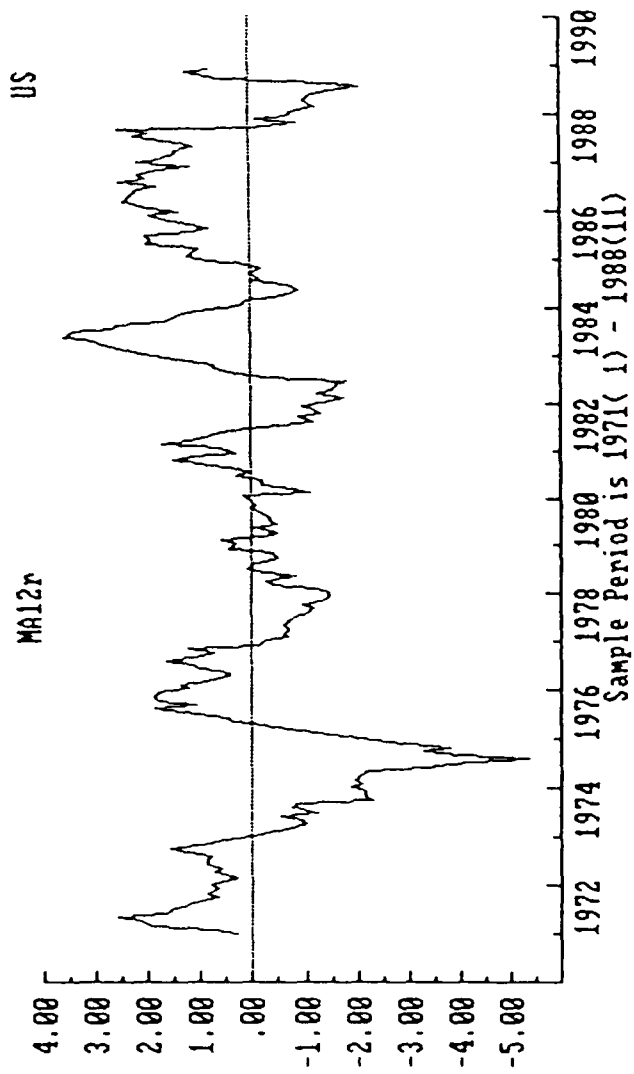
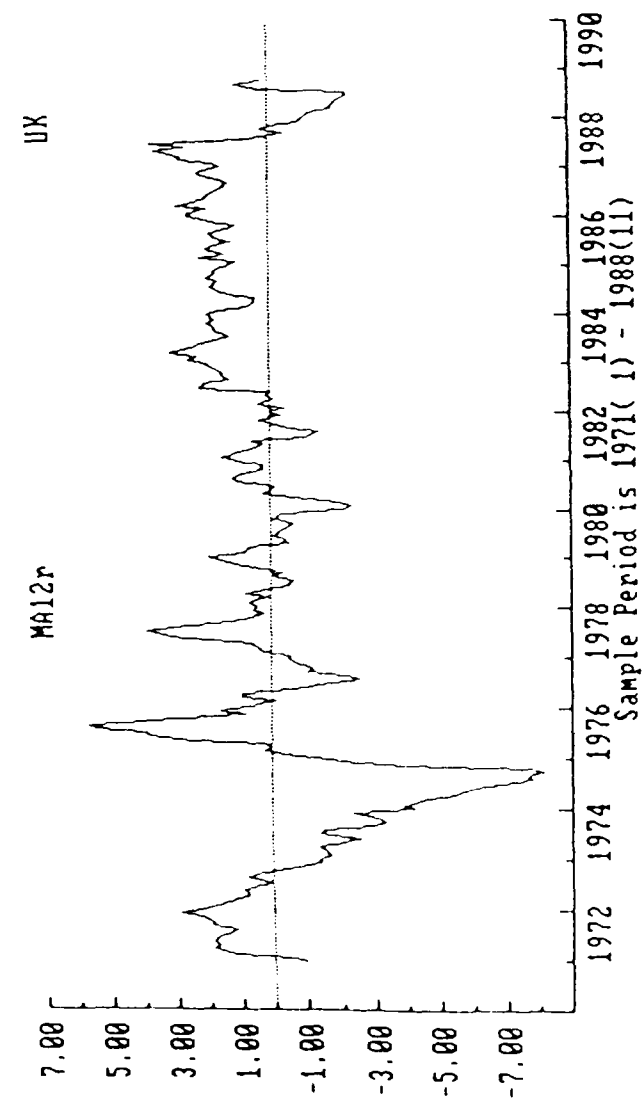
Sample means and standard deviations of variables.<sup>5</sup>

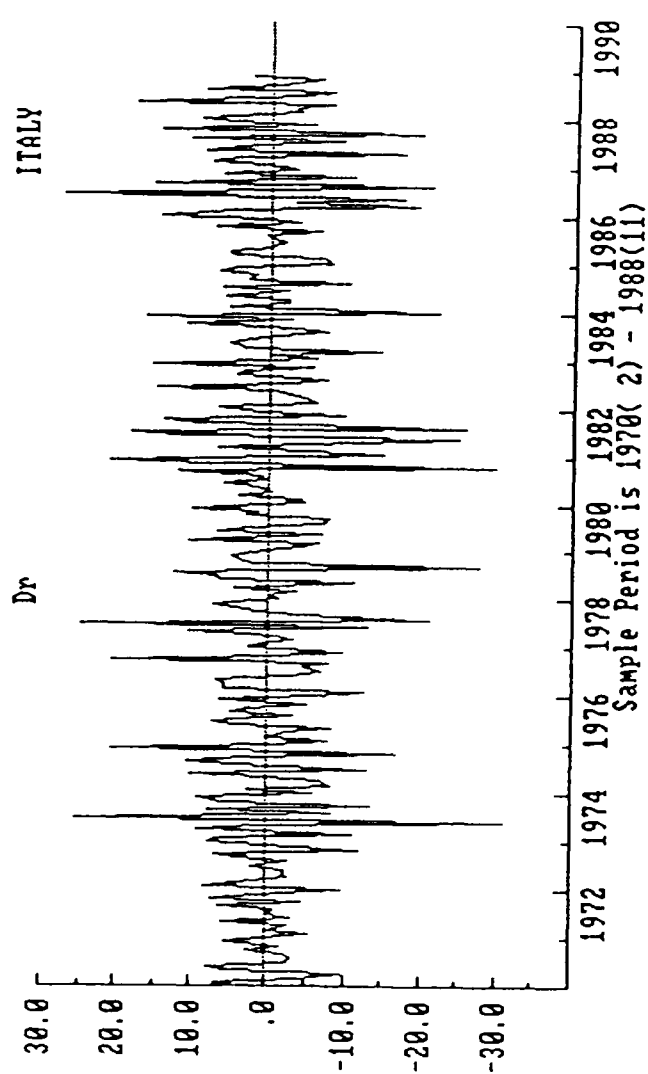
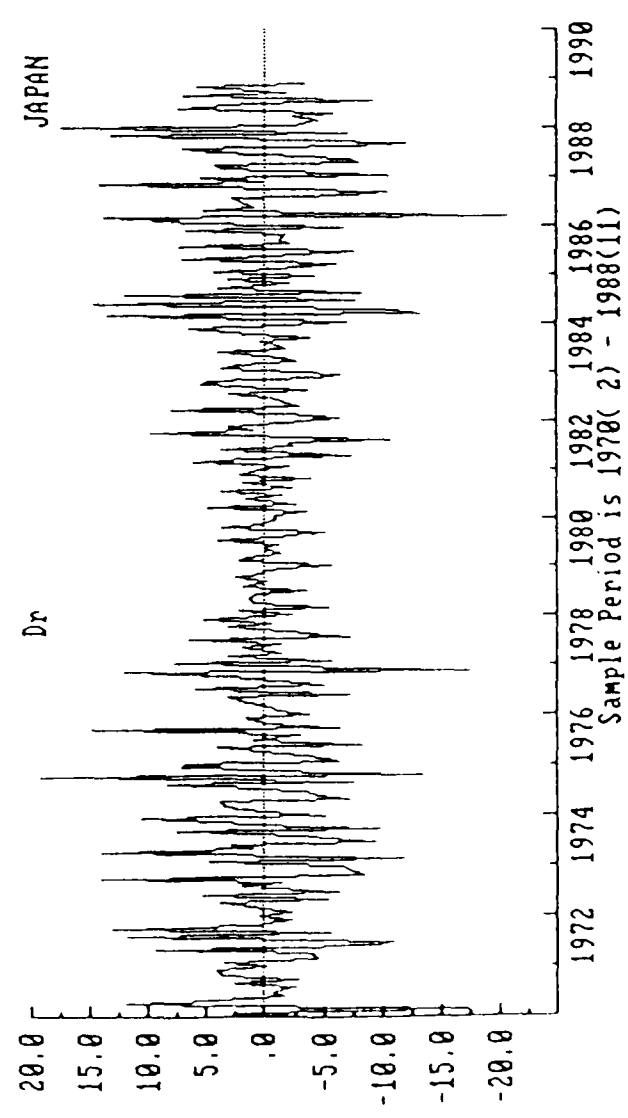
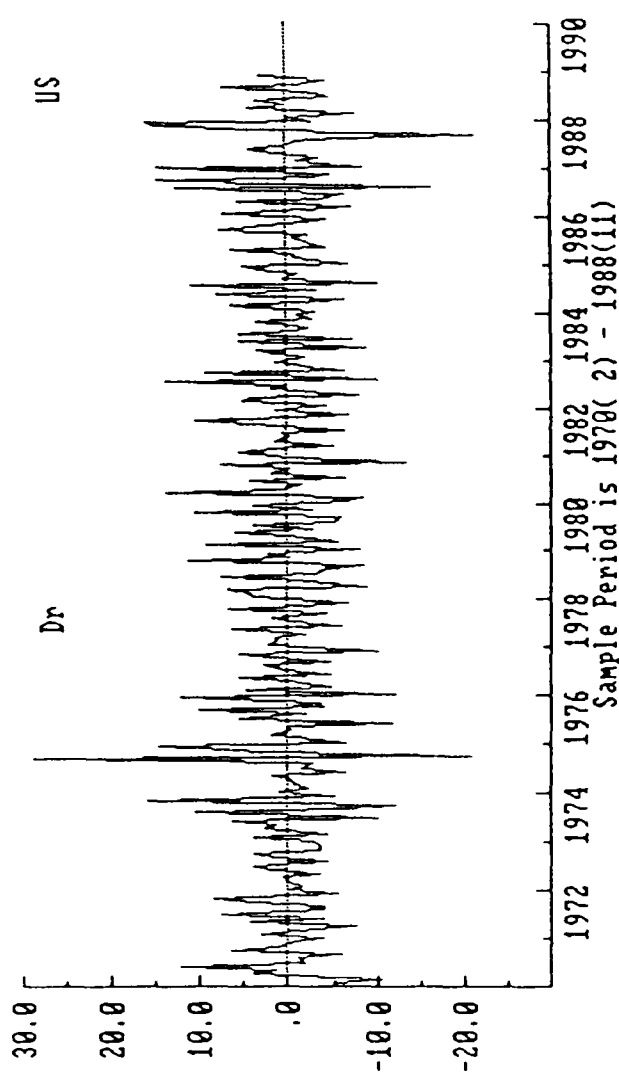
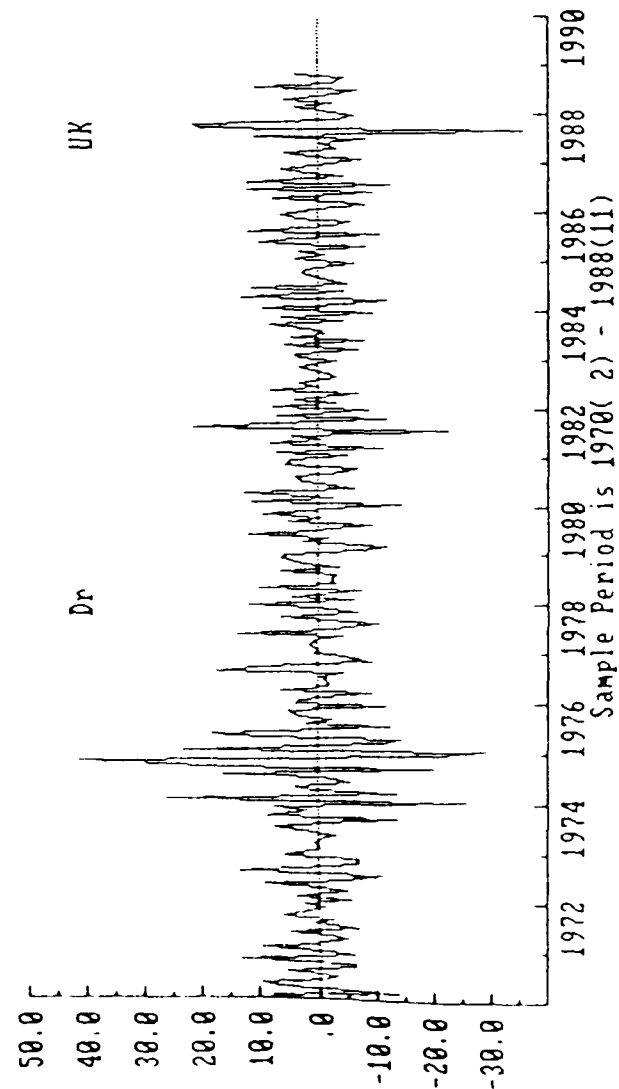
|            | UK    |          | US    |          | JAPAN |          | ITALY |          |
|------------|-------|----------|-------|----------|-------|----------|-------|----------|
|            | m     | $\sigma$ | m     | $\sigma$ | m     | $\sigma$ | m     | $\sigma$ |
| r          | .24   | 6.83     | .19   | 4.86     | .86   | 4.98     | -.12  | 7.18     |
| MA12r      | .32   | 2.14     | .21   | 1.47     | .90   | 1.82     | -.12  | 2.86     |
| $\Delta r$ | .027  | 9.12     | -.016 | 6.62     | .012  | 6.55     | .019  | 9.44     |
| MSD12r     | 5.83  | 3.02     | 4.37  | 1.54     | 4.33  | 1.62     | 6.39  | 2.00     |
| INF        | 10.18 | 5.87     | 6.41  | 3.30     | 6.03  | 5.77     | 11.39 | 5.03     |
| MSD12INF   | 1.55  | 1.05     | .83   | .42      | 1.30  | 1.29     | 1.23  | .84      |
| DY         | 5.30  | 1.33     | 4.27  | .85      | 1.64  | .64      | 2.72  | 1.20     |
| BY         | 11.67 | 2.23     | 9.14  | 2.34     | 7.26  | 1.24     | 12.42 | 4.12     |
| LOCUS      | 5.93  | .21      |       |          | 5.94  | .40      | 5.49  | .38      |
| LOCUSM     | .006  | .093     |       |          | .039  | .094     | -.016 | .156     |

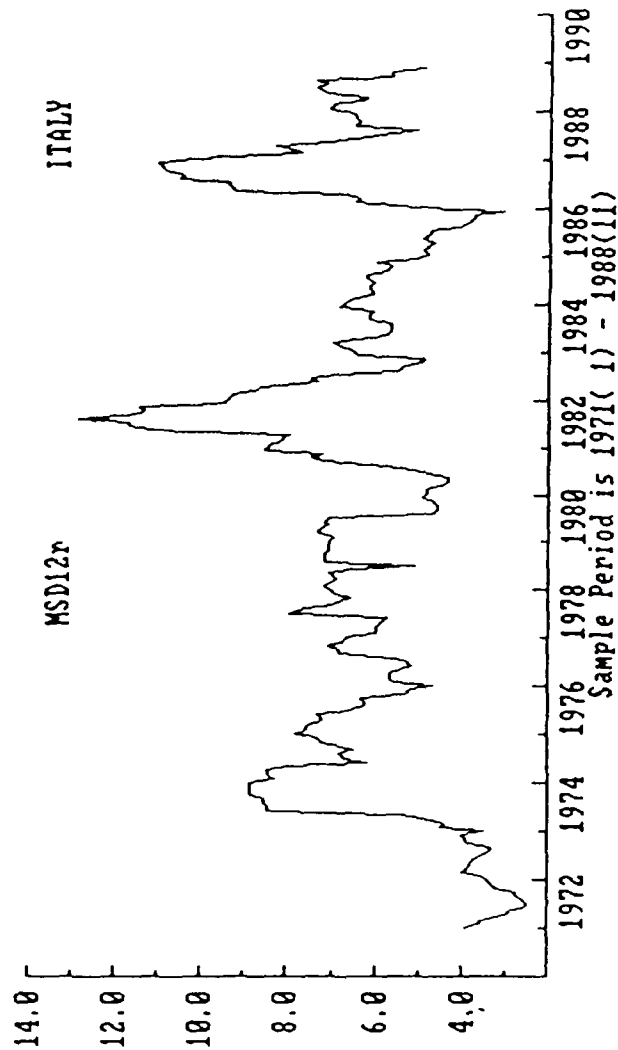
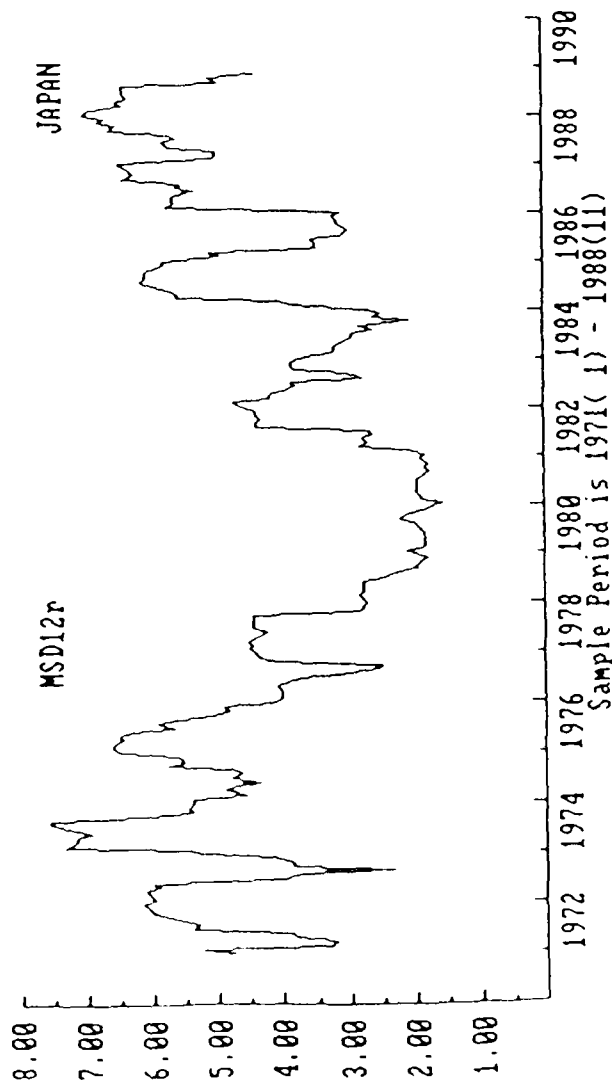
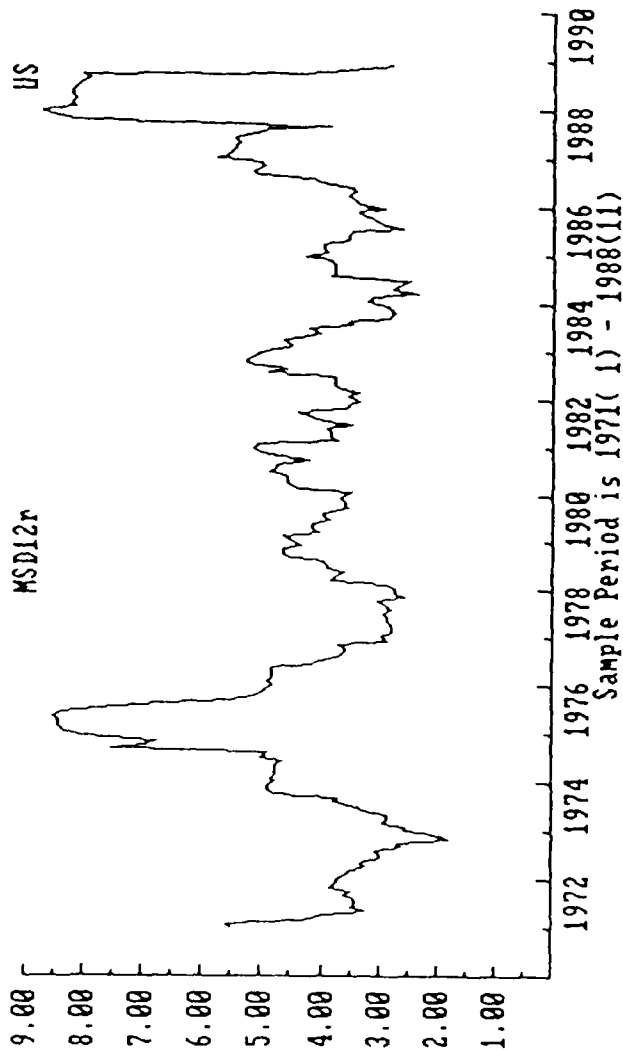
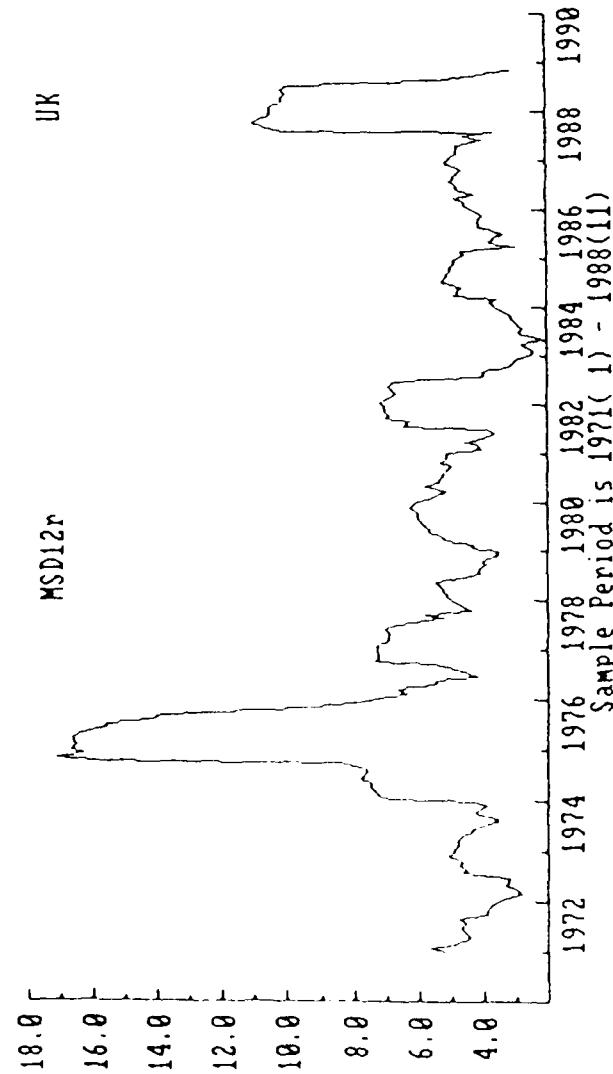
5. Means and standard deviations are from 1970(1) for r, INF, BY and LOCUS, from 1971(1) for MA12r, MSD12r, MSD12INF and LOCUSM, from 1973(1) for DY and from 1970(2) for  $\Delta r$ .

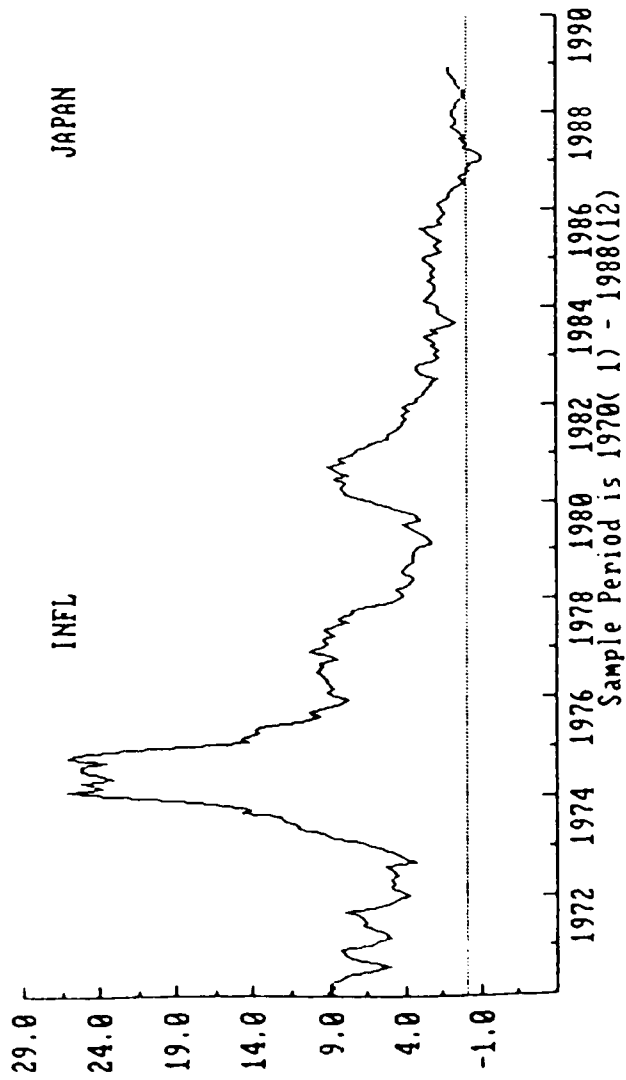
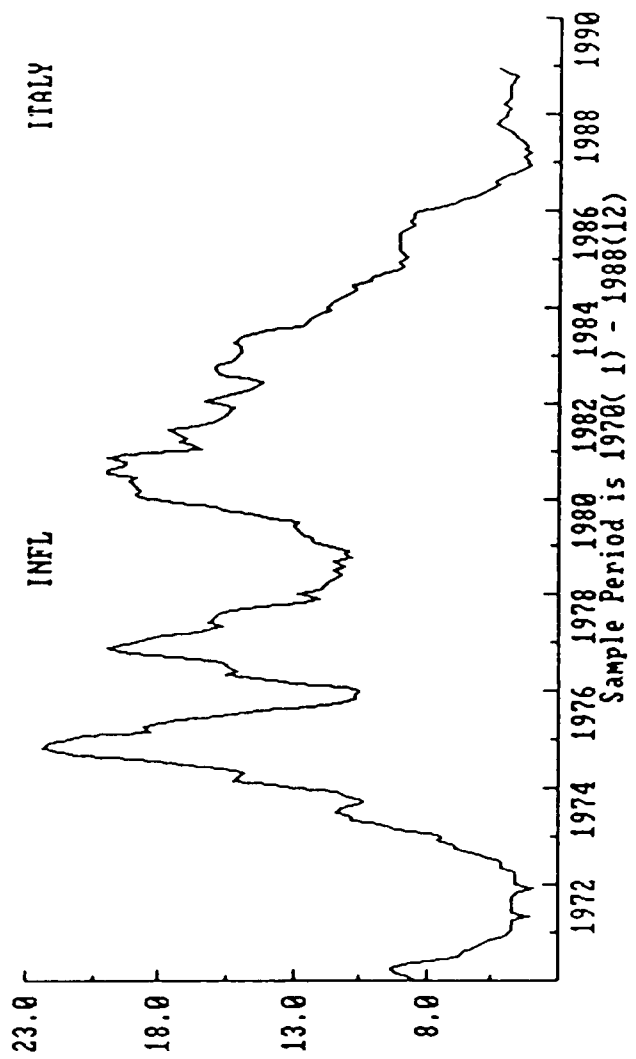
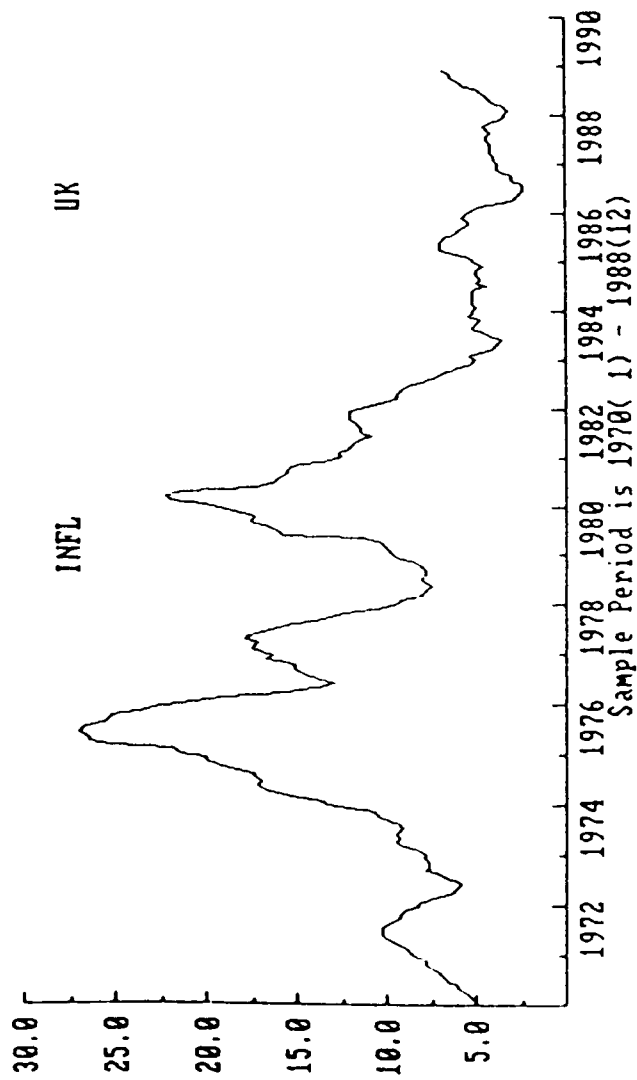
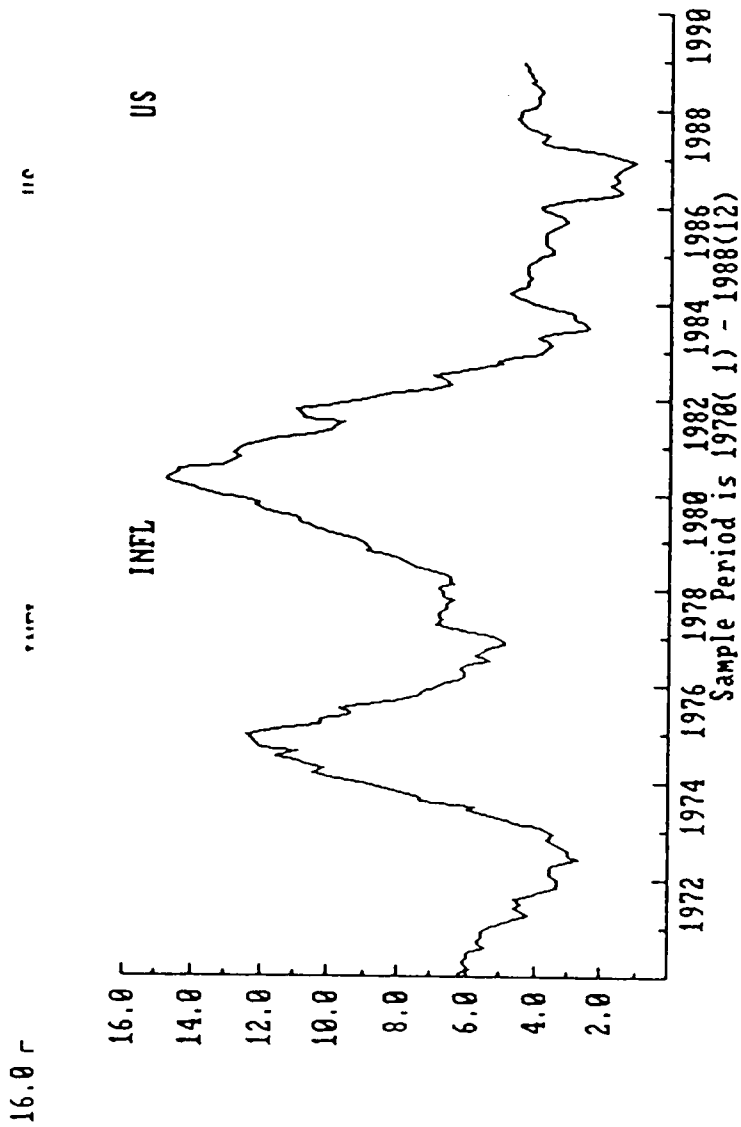


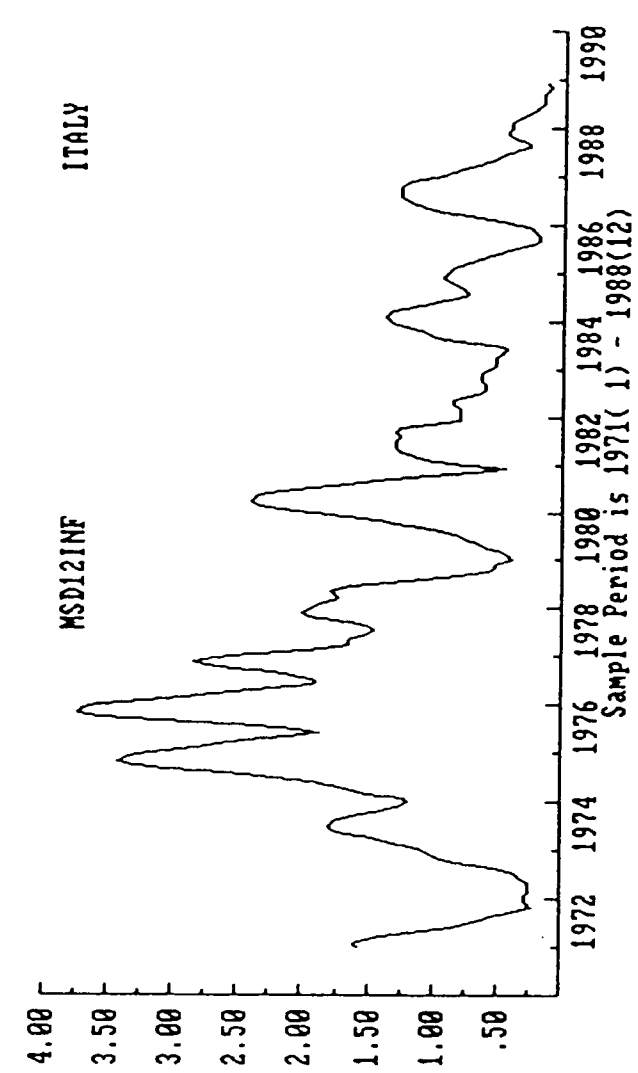
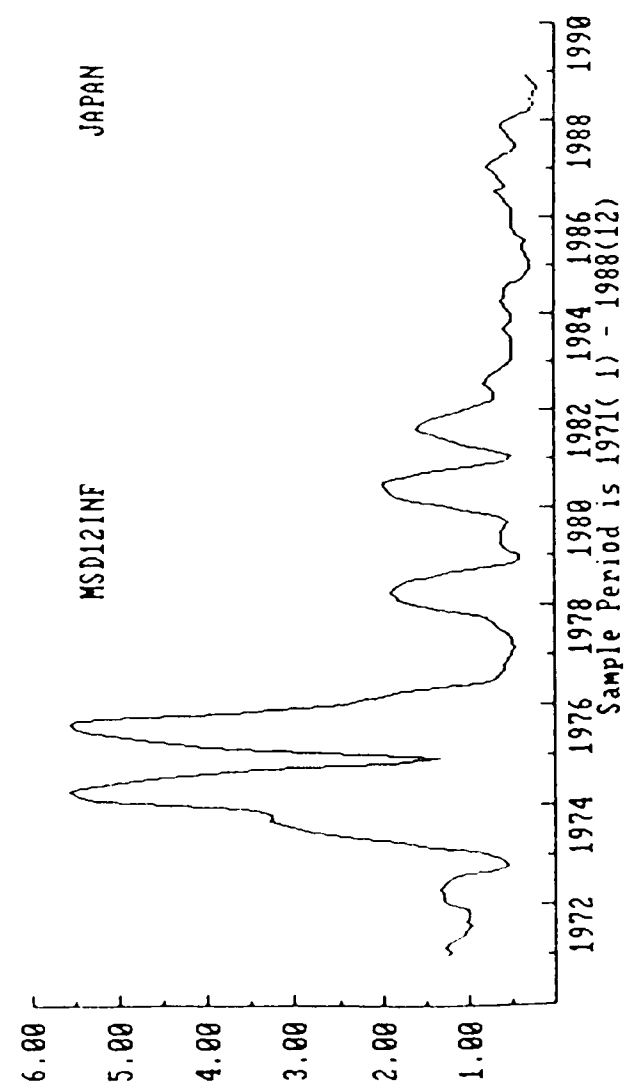
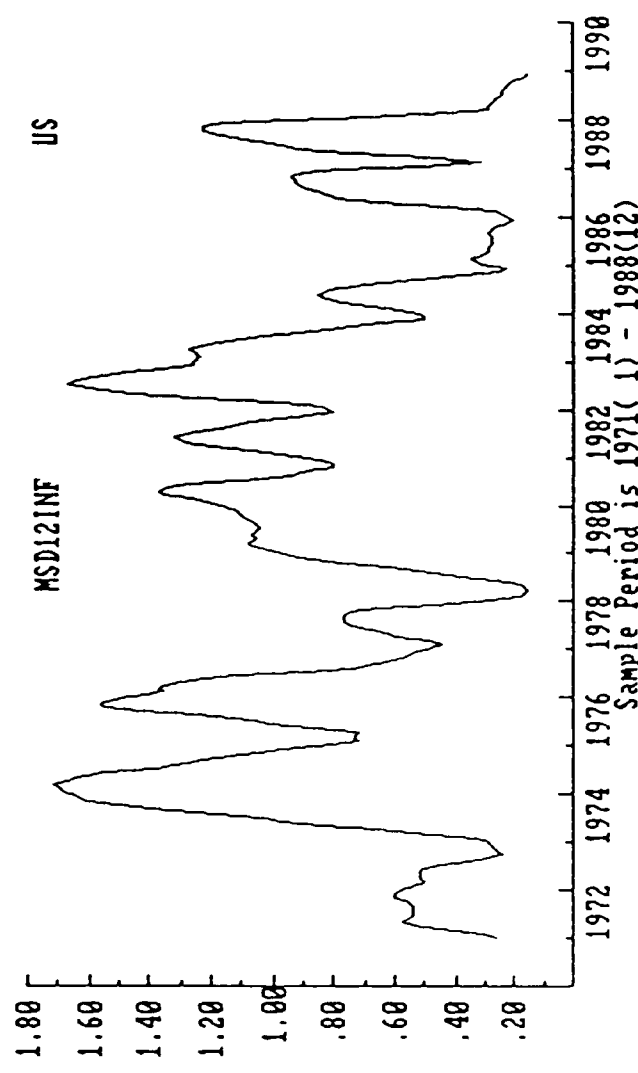
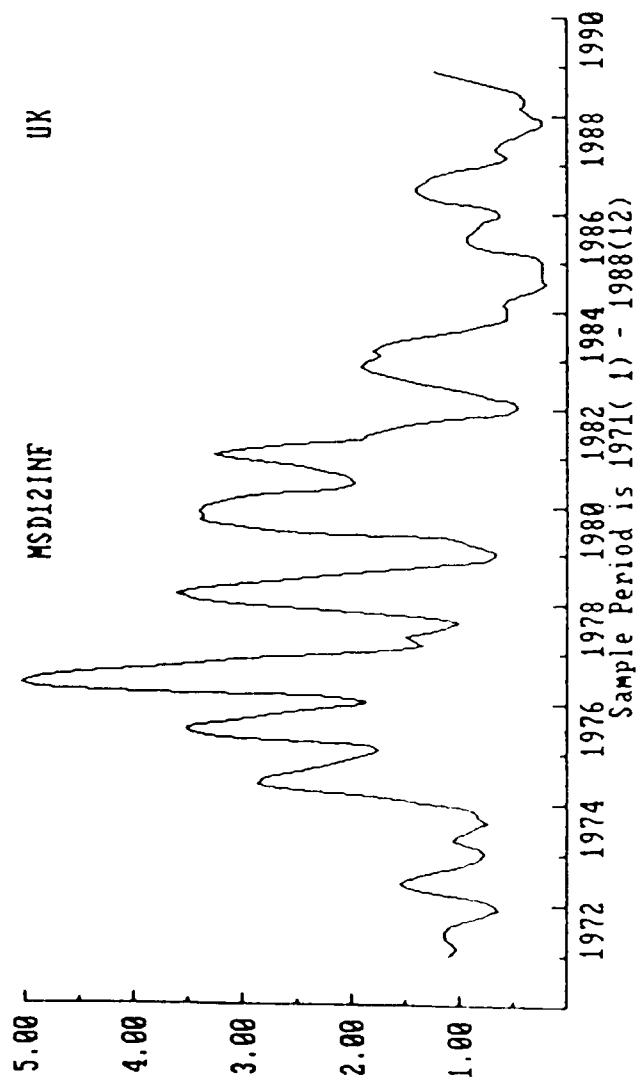


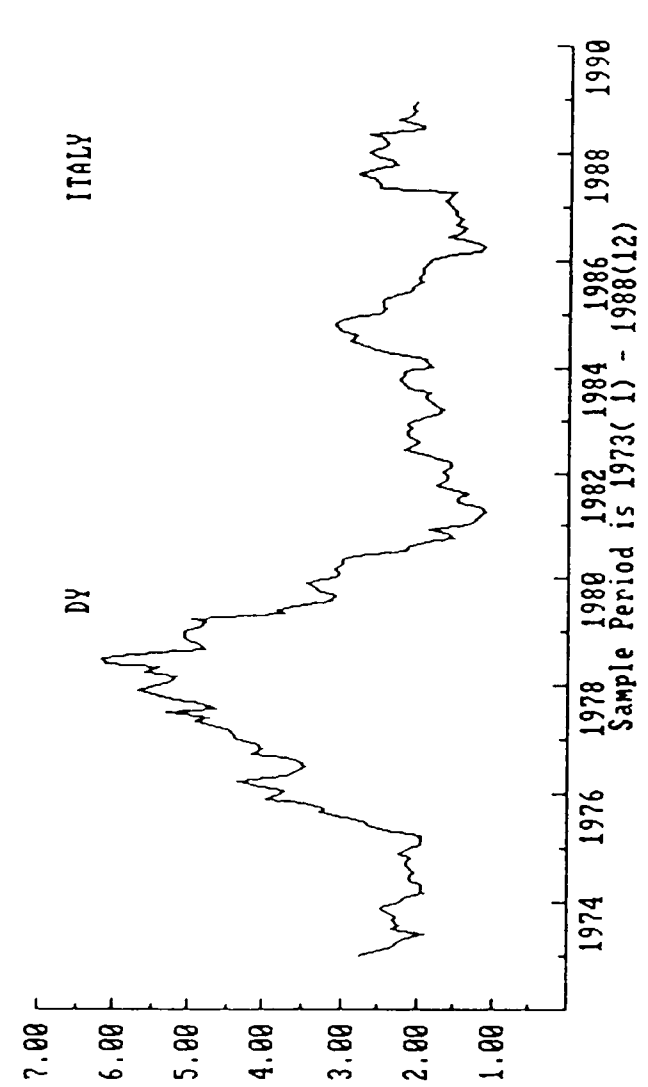
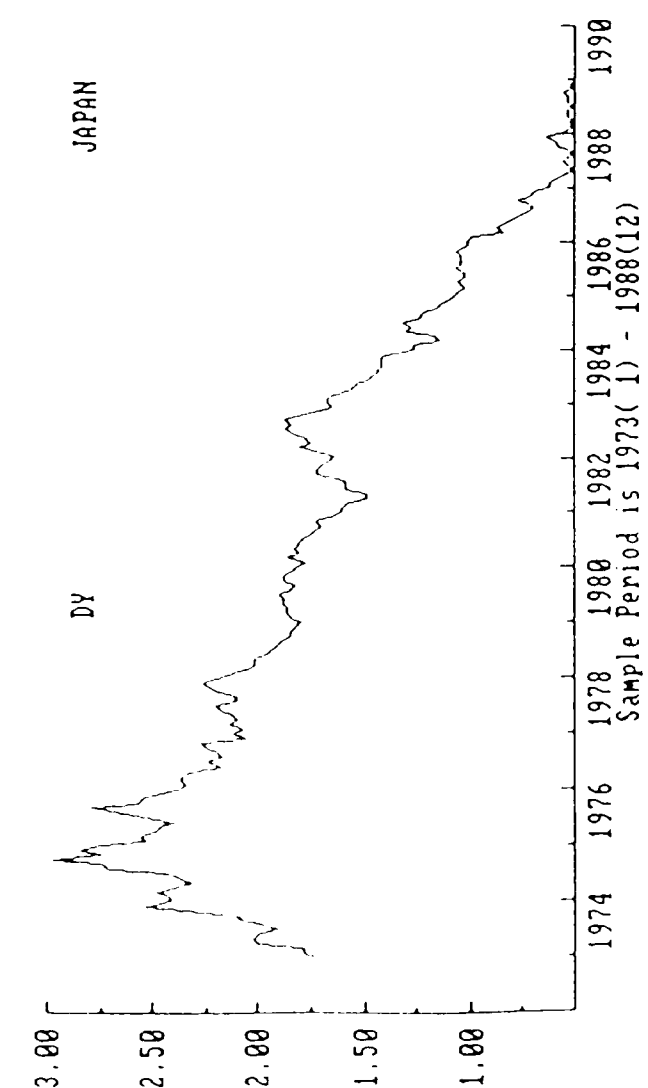
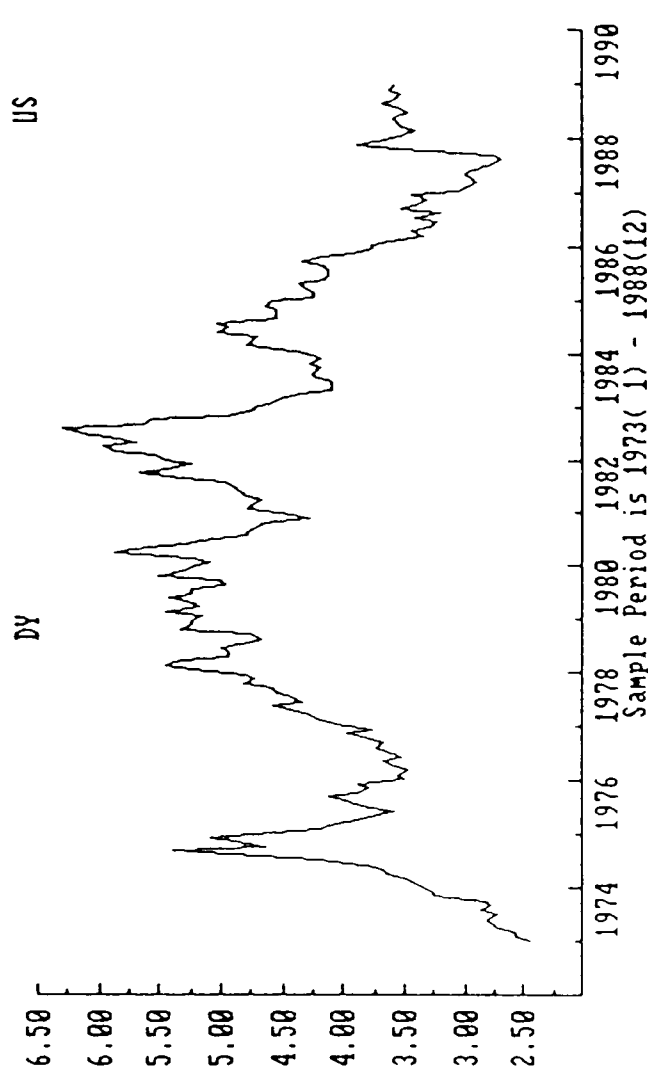
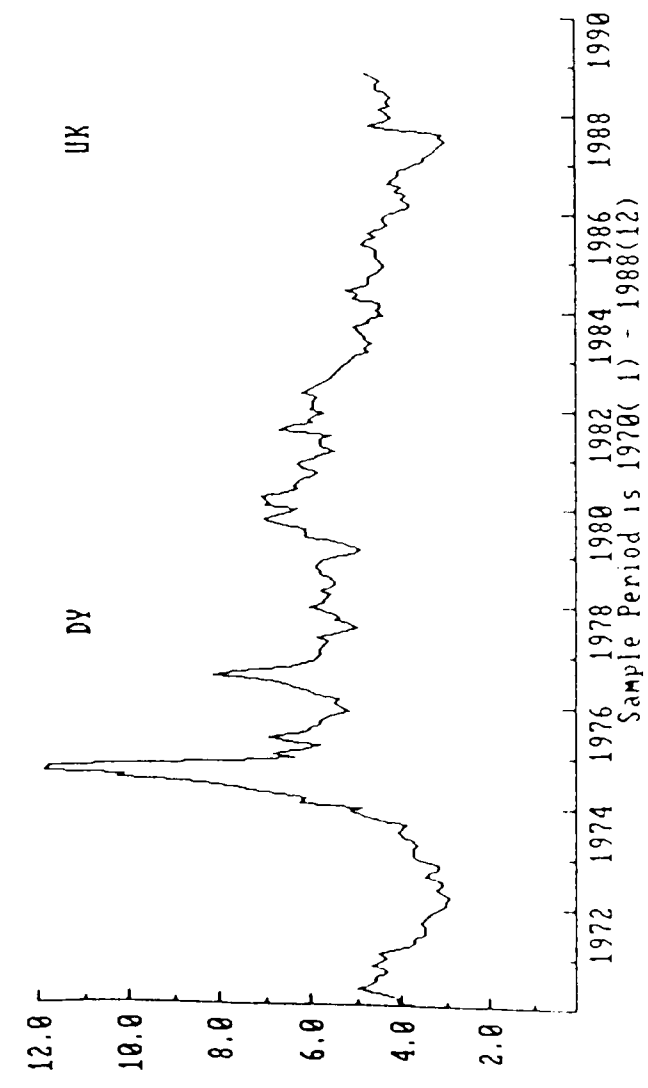


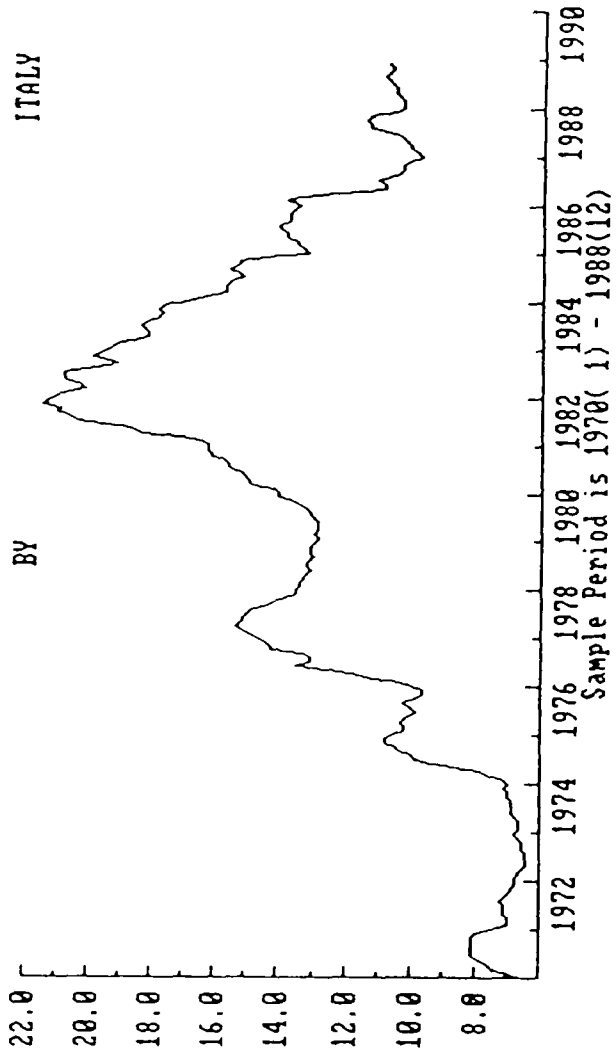
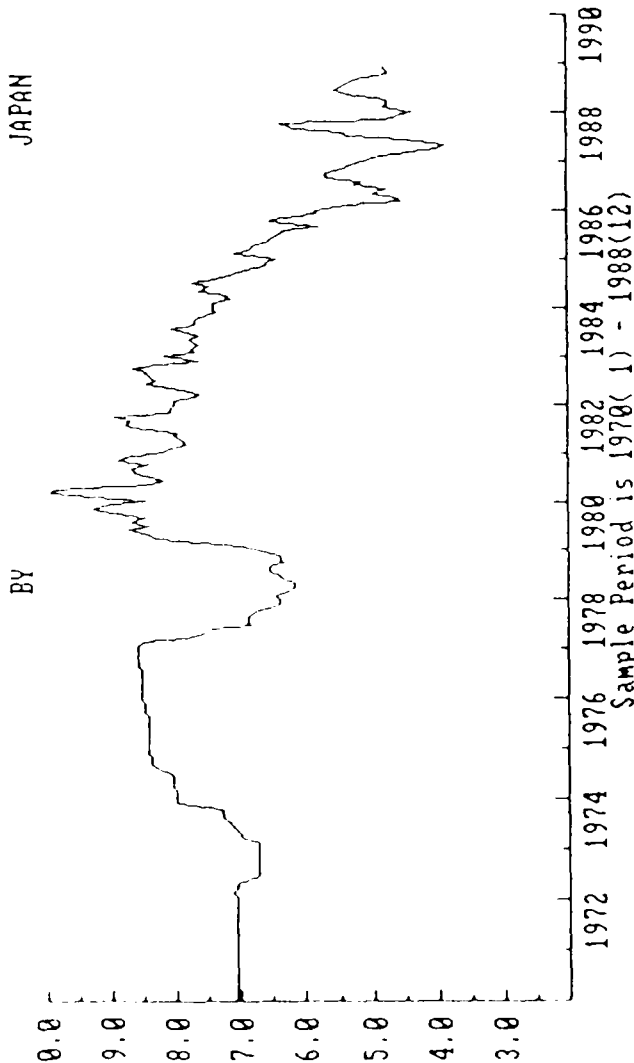
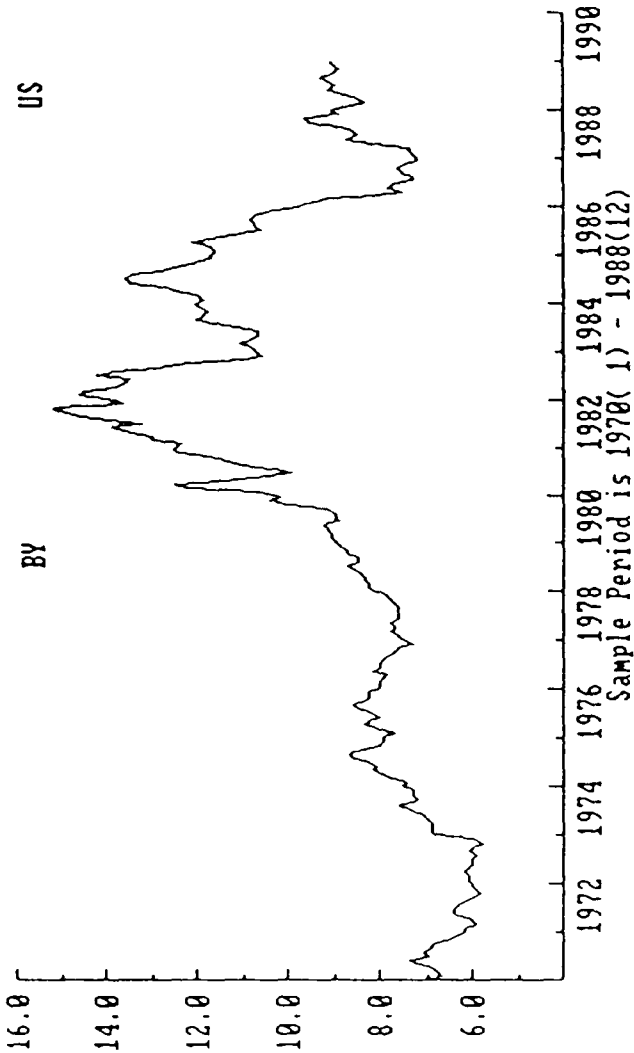
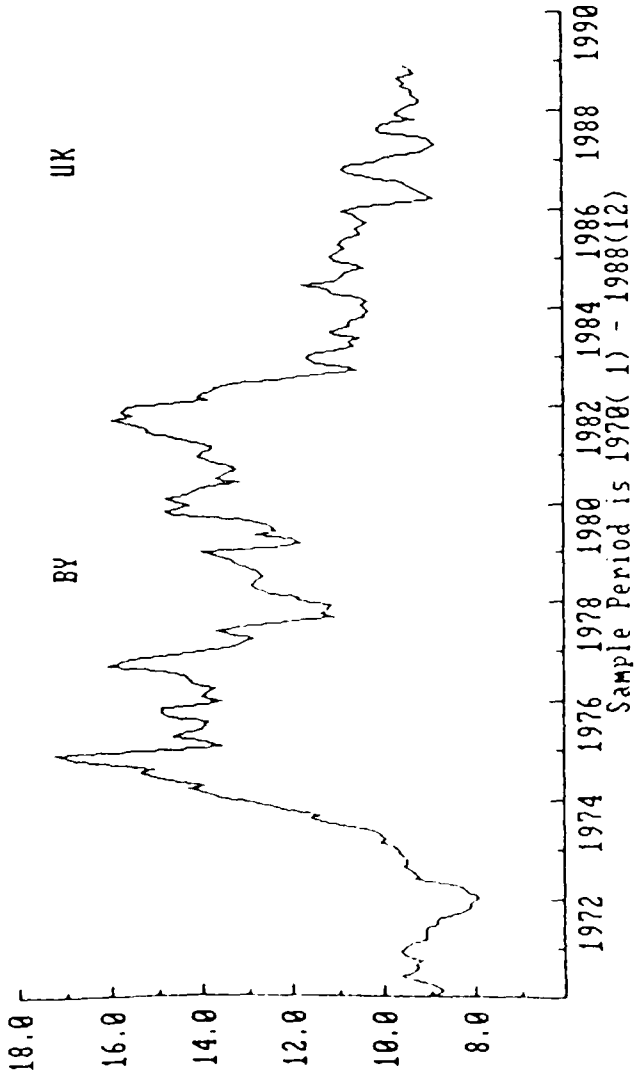


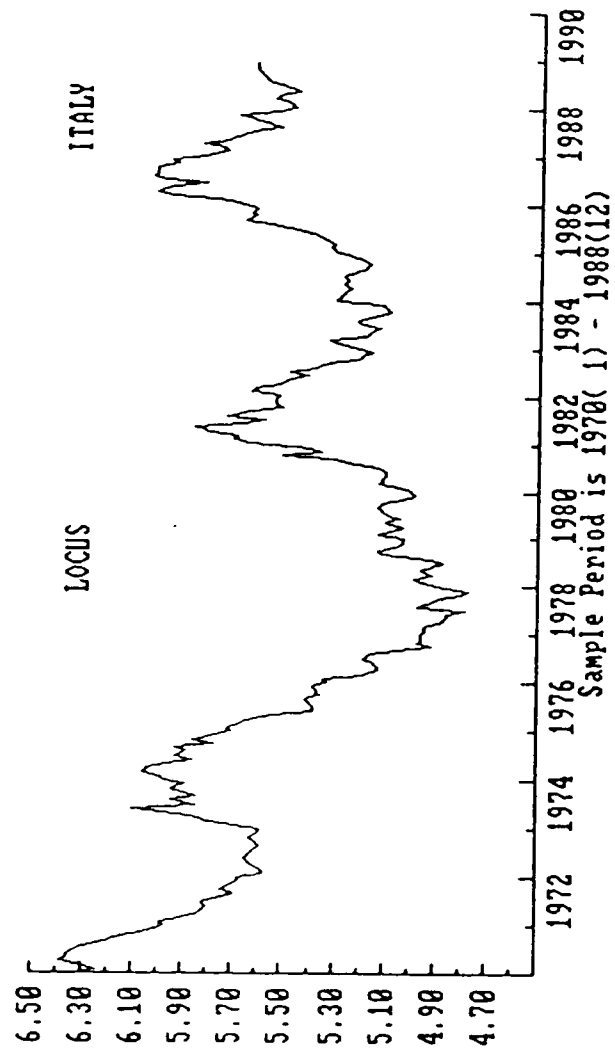
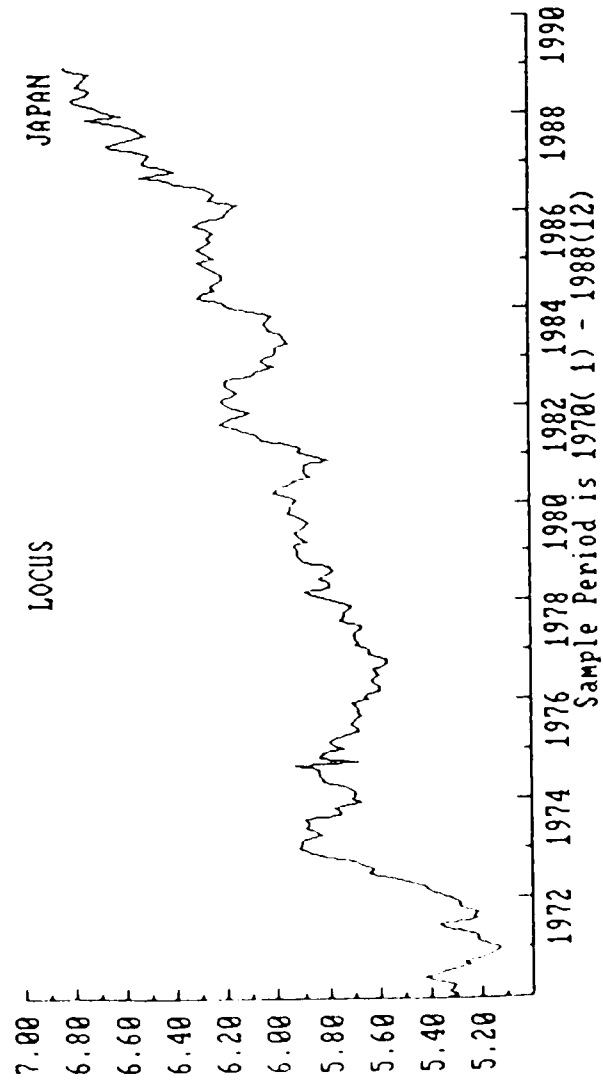
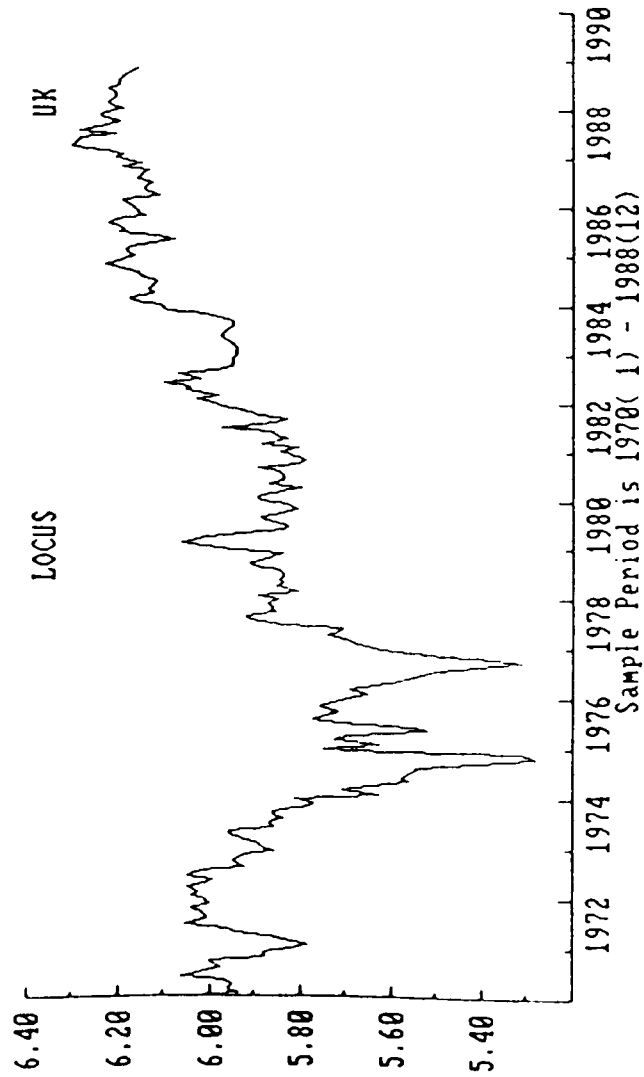


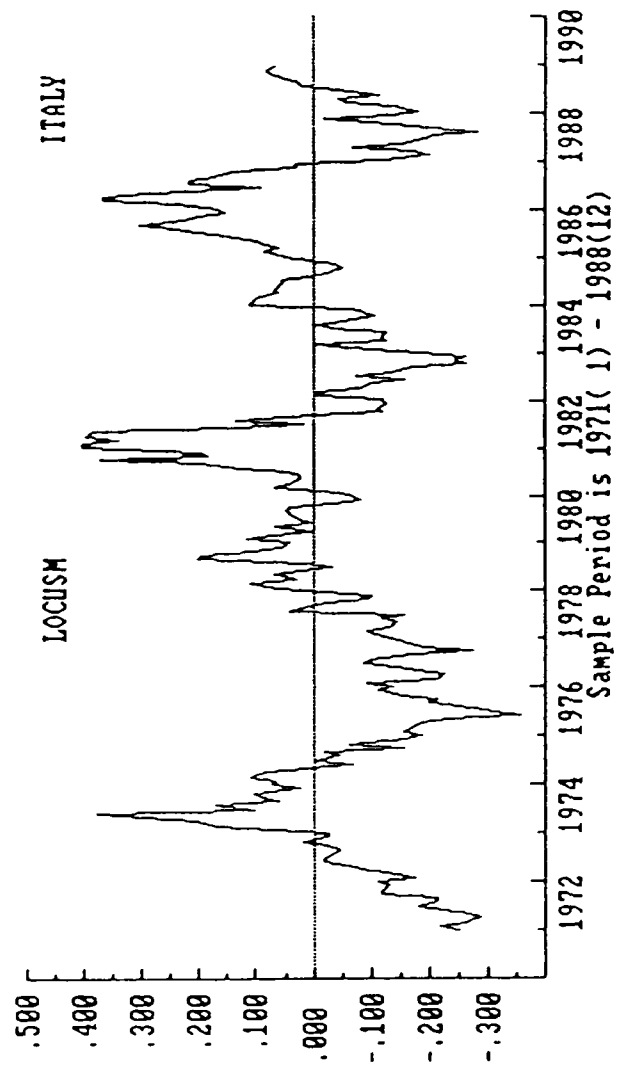
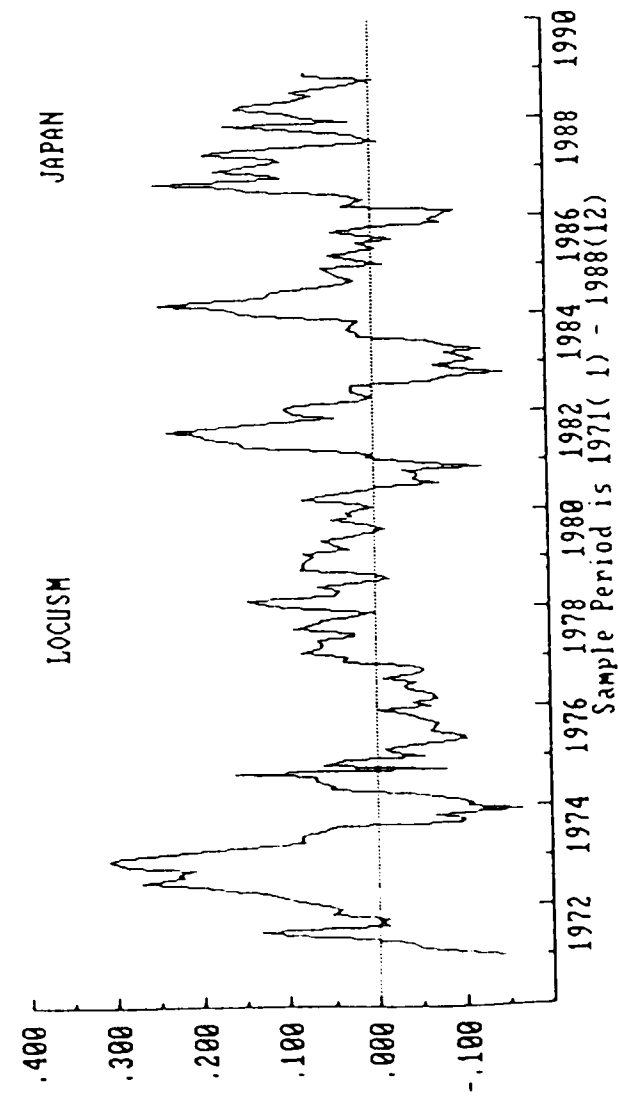
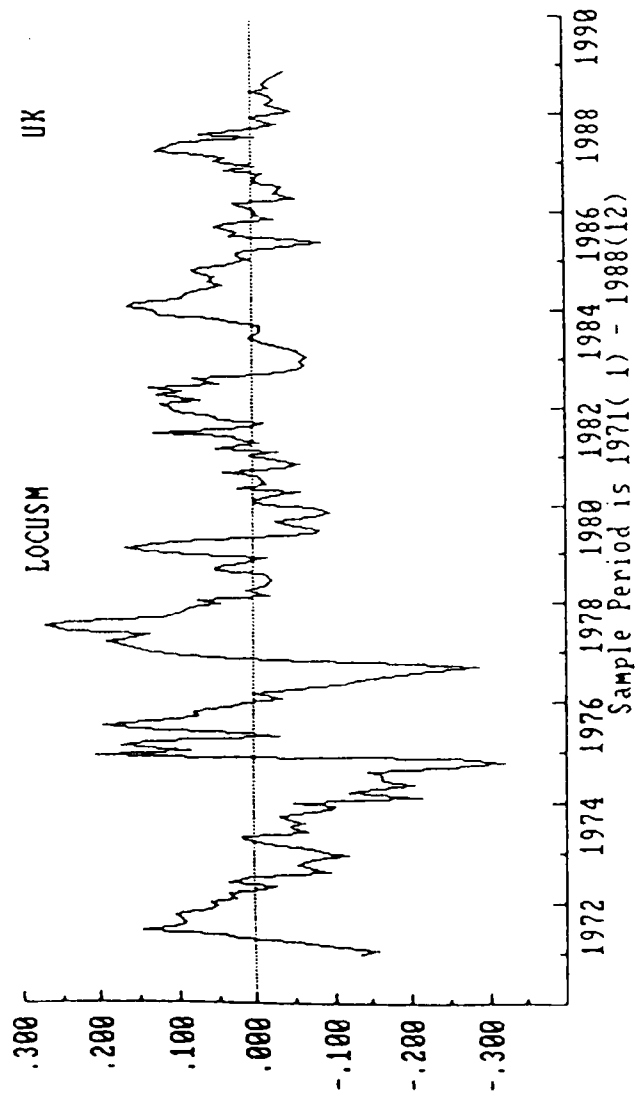


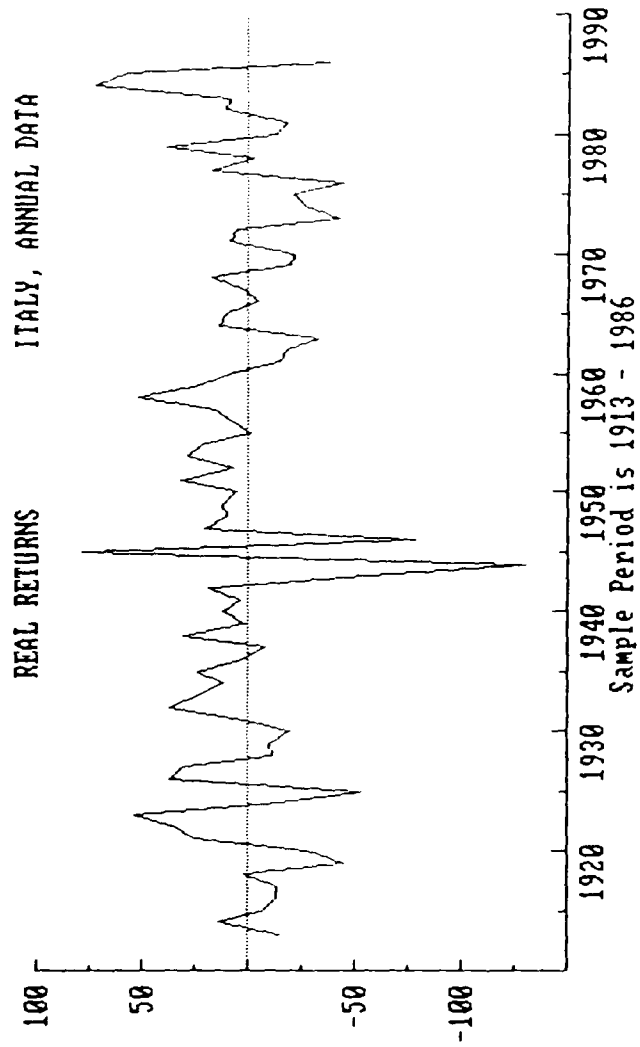
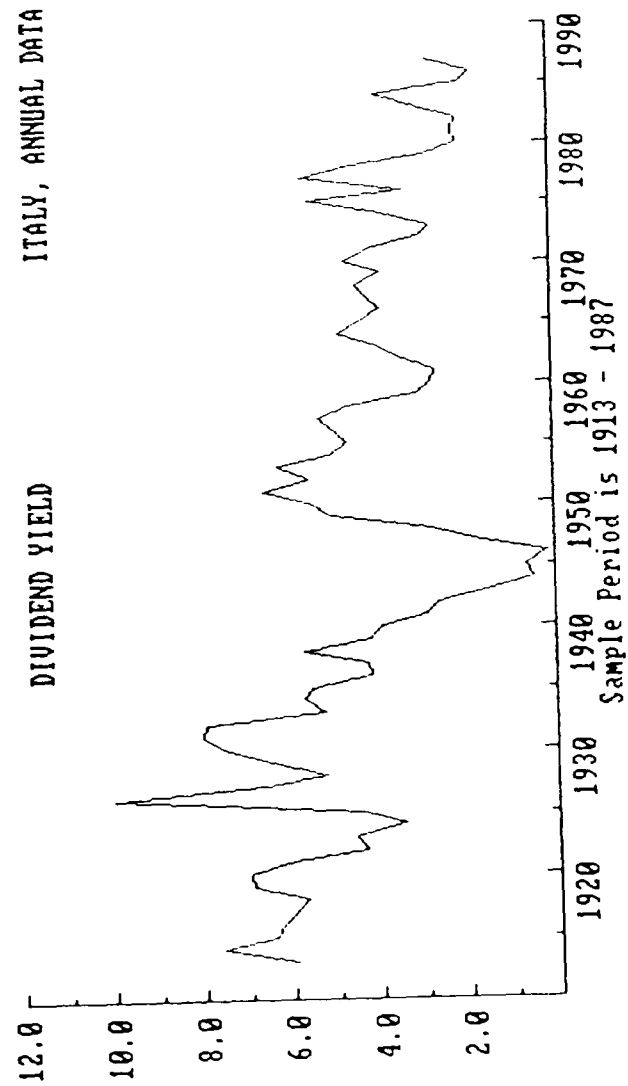
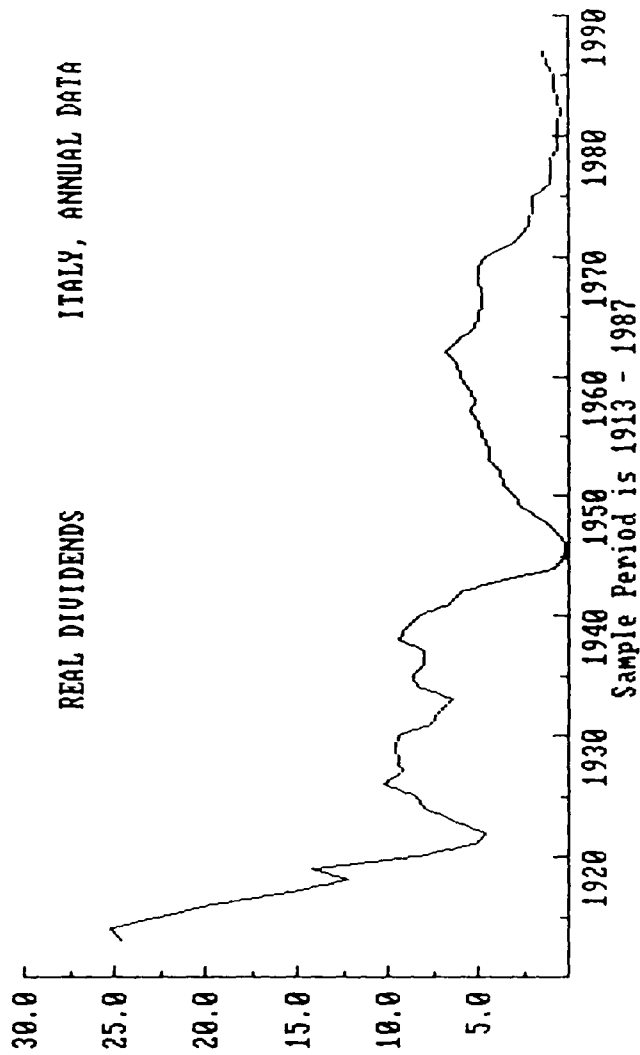
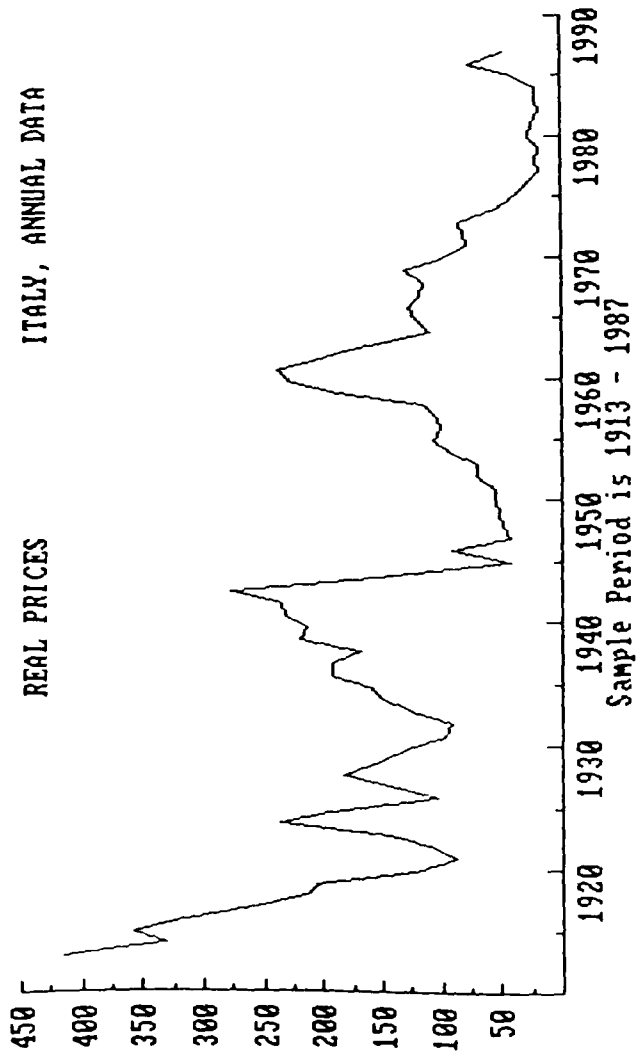












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