Essays in Macroeconomic and Financial Linkages

by

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ABSTRACT

This thesis presents a number of essays on the linkages between macroeconomic time series and stock price behaviour. Three general areas are examined: mean reversion and predictability in stock prices, the stock return-inflation puzzle, and the present value model of stock prices. A macro model with overlapping wage contracts and a stock price determination equation motivates five empirical essays; three are associated with mean reversion. Employing recent econometric techniques, estimating a restricted multivariate VAR decomposition shows that real stock prices exhibit significant temporary and permanent components that are attributed to aggregate demand and supply innovations, respectively. The temporary component is by definition mean-reverting. The first empirical essay considers monthly US stock prices, pre- and post-war periods. This is extended to a multi-country analysis in the second essay. The third empirical essay investigates the dynamic relationship between real stock prices and interest rates. The mean-reversion hypothesis is examined using a decomposition method to estimate the temporary and permanent components of US and UK real stock prices. The fourth empirical essay shows that the stock return-inflation puzzle can be explained by decomposing inflation into two counterfactual series - one due to aggregate demand innovations and the other due to aggregate supply innovations. The results indicate that real stock returns are negatively correlated with inflation due only to aggregate supply innovations and not correlated with inflation due to aggregate demand innovations. This supports Fama's proxy hypothesis explanation of the puzzle. The final empirical essay examines the present value model. The findings reveal that adjustment of stock prices to the long-run equilibrium - identified by the present value model - is nonlinear and is approximated well by an ESTAR-ARCH model. This finding is consistent with microstructure features of the stock market, such as transaction costs and limits to arbitrage, and is further supported by illustrative Monte Carlo evidence.

Chapter 1

INTRODUCTION

The importance of innovations in macroeconomic time series in financial markets is addressed by investigating a number of key issues in stock price behaviour. Three general areas are examined: mean reversion and predictability in stock prices, the stock return-inflation puzzle, and the present value model of stock prices. A central theme of the traditional literature on stock price behaviour is that stock prices follow a random walk. Motivated by recent evidence in favour of mean reversion in stock prices and econometric techniques, this view is challenged by examining the dynamic behaviour of stock prices to macroeconomic shocks. In contrast to previous studies that have examined mean reversion, this thesis employs the interaction between macroeconomic time series and stock prices to investigate the mean reversion hypothesis. Empirical evidence on mean reversion is provided in Chapters 5-7.

There are a number of hypotheses put forward to explain the puzzle that stock returns and inflation are negatively correlated. Motivated by the limitations of the underlying theoretical and empirical explanations, we investigate the puzzle using a macroeconomic model that incorporates a stock price determination equation and, unlike previous studies, the model is Fisherian in structure. A multivariate regression approach is employed to empirically analysis U.S. data.

The present value model of stock prices has proven to be very popular in finance, in particular in modelling market efficiency. Recently, however a number of studies have shown that the present value model is rejected when strong tests of the model are examined. Cointegration and Granger-causality tests support the present value model. In contrast, cross-equation restrictions tests reject the model. Motivated by this finding and market microstructure aspects of the stock price literature, we explore the hypothesis that the equilibrium error is non-linear and is approximated well by an exponential smooth transition autoregressive model.

The layout of the thesis is as follows. The objective of Chapter 2 is to present an extensive literature review on mean reversion in stock prices, in a concise and consolidated manner. This literature also embodies the associated literature on stock price predictability. The intuition of mean reversion is that stock prices contain both a permanent and temporary component. The temporary component is a mean-reverting component, that is, the market value of common stocks deviate from their fundamental values but will revert to their mean. Since the temporary component is stationary it implies that stock returns are to some degree predictable. Alternative theories to the random walk hypothesis offer insights into the reason why stock prices might contain a mean-reverting component. These theories are explored in Chapter 2.

An implication of the mean-reversion hypothesis is that stock prices exhibit negative serial correlation at long stock return horizons. The empirical literature on mean reversion tends to rely on one of two related multi-period testing methodologies: the Fama and French (1988a) regression-based test and the variance-ratio test (Cochrane, 1988). The reliability of these multi-period return tests has recently being questioned and more recently, vector autoregressive analysis has been used to identify the temporary component of stock prices. The theoretical and empirical issues associated with these testing methodologies are outlined in sections 2.2-2.4. Chapter 2 provides part of the background for the empirical work presented in Chapters 5, 6 and 7.

The information contained in macroeconomic variables is used to investigate whether stock prices contain a temporary component and are, therefore, mean reverting. In order to illustrate and identify the relationship between macroeconomic and financial time series, Chapter 3 outlines a simple log-linear macro model with overlapping nominal wage contracts and a real stock price determination equation. The model is essentially neoclassical and Fisherian in structure and allows reasonably complex dynamics.

In Chapter 3 we have two objectives. First, using a simple macro model with overlapping nominal wage contracts, we demonstrate that changes in log real stock prices may be serially correlated even under the assumption of fully efficient markets in the sense that there are no profitable arbitrage opportunities between current and expected stock price movements. Second, we show how the temporary and permanent components of stock price movements may be related to aggregate macroeconomic supply and demand disturbances. In particular, in the context of the same macro model, we show that aggregate demand shocks have only temporary effects on real stock prices, while supply shocks may affect the level of real stock prices permanently. The model is simulated to derive real stock prices, consumer prices and real output series that are used to evaluate the proportion of variation in real stock prices explained by aggregate demand shocks. The simulated model is also used in Chapter 9 to examine the stock return-inflation puzzle - the correlation between real stock returns, inflation, and real output growth.

The empirical chapters 5-7 and 9 rely on a related econometric technique. One of the objectives of Chapter 4 is to give a detailed exposition of this technique. We consider a variant of the Blanchard and Quah (1989) multivariate econometric technique of decomposing a series into its temporary and permanent components. Since the empirical work in the later chapters requires an examination of two shocks - the simple macro model, presented in Chapter 3, identifies these two shocks as aggregate (macroeconomic) demand and supply shocks - to real stock prices and macroeconomic time series, we require a two variable vector autoregressive (VAR) system to decompose the series in question. Thus, this chapter examines the decomposition of a 2×1 vector of time series. We also compare the VAR decomposition to the derivation of a pure random walk component in the vector.

A characteristic of most financial time series is that the disturbances are non-Gaussian, and in the presence of errors that are not normally distributed (for example, a leptokurtic distribution) can lead to estimates that are extremely fragile. For this reason, in Chapter 4 we give an overview of two robust estimation procedures - the least absolute deviation (LAD) estimator and the residual augmented least squares (RALS) estimator - that we employ in the empirical work in examining the dynamic behaviour between interest rates and real stock prices, Chapter 7. The RALS estimation procedure is very recent and a detailed explanation is provided. Furthermore, as illustrated in Chapter 4, the RALS procedure allows a more powerful test for unit roots, than the standard Dickey-Fuller test, when the error sequence is driven by non-normal errors.

The empirical aspect of this study relies on a number of data sources, including the International Monetary Fund's International Financial Statistics data base, the Chicago University Center for Research in Security Prices (CRSP) Indices File, and Datastream. Emphasis is placed on US estimation as this allows for a greater comparison with previous work and because of high quality non-overlapping long time series for US stock prices.

Chapter 5 uses a restricted two-variable - real stock prices and consumer prices - vector autoregressive system, a variant of the Blanchard-Quah technique, to decompose real US prices into two components - a component that does not have a long-run effect on stock prices (temporary component) and a component that has a long-run effect on stock prices (permanent component). In the context of the macro model, aggregate macroeconomic demand shocks have only temporary effects on real stock prices, that is, stock prices are mean-reverting, while aggregate supply shocks affect the level of real stock prices permanently.

Thus, we interpret the temporary component as the response of stock prices due to aggregate demand innovations and the permanent component as the response of stock prices due to aggregate supply innovations. The interrelationship between macroeconomic and financial time series allows us to estimate a temporary component in real stock prices that is mean reverting. We then go on to investigate the size and significance of this mean-reverting component in US stock prices, for the 1925:1-1995:12 period, by placing appropriate structural restrictions on a VAR of real stock prices and consumer prices corresponding to the simple macro model in Chapter 3.

The empirical investigation of macroeconomic shocks to real US stock prices and the estimation of the size and significance of a mean-reverting in stock prices is extended in Chapter 6 to examine sixteen countries.[1] This offers much broader international evidence on macroeconomic shocks to stock prices and the size of the mean-reverting component of stock prices than has been hitherto available. In selecting the international data we chose quarterly data on stock prices, since these were available for a number of countries on a continuous basis from as early as 1957. As in Chapter 5 we employ a multivariate time series technique based on the VAR of real stock prices and consumer prices - as outlined in Chapter 4 - to decompose real stock prices. A comparison of the results yields some interesting insights into the nature of the linkages between macroeconomic

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[1]The following countries were included in the study: Austria, Belgium, Canada, Finland, France, Germany, India, Italy, Japan, Netherlands, Norway, South Africa, Sweden, Switzerland, the UK, and the US.

and financial time series.

In Chapter 7 we investigate the interaction between stock price and interest rate movements in assessing the size, significance and persistence of the mean-reverting component in UK and US real stock prices. We specify a VAR of real stock prices and nominal interest rates and employ the econometric technique as outlined in Chapter 4 to identify temporary and permanent innovations in real stock price movements. In the context of the estimated VAR, we exploit the dynamic relationship between interest rates and stock prices, illustrated by the present value model, to identify the temporary and permanent shocks to real stock prices. The temporary shock to real stock prices will cause stock prices to rise initially and then to reduce so that it has a zero long-run effect. On the other hand, a permanent shock increases the real stock price in both the short run and long run. We also expect a permanent shock to decrease interest rates, while a temporary shock will increase interest rates.

Given the evidence that innovations in financial asset prices exhibit non-normal distribution properties we investigate the sensitivity of the size, significance and persistence of the mean-reverting component to two robust estimation procedures - the LAD and RALS methods - as identified in Chapter 4, in order to allow for possible non-normality of the innovations to stock returns and interest rates.

The influential work of Irving Fisher *The Theory of Interest* (1930) has generated a voluminous amount of research, especially in relation to the inflation-interest rate puzzle. The hypothesis postulated by Fisher has taken many forms, including generalizing the relationship to all assets. It is the inflation-stock return puzzle that we consider in Chapters 8 and 9.

The basic premise of the generalized Fisher hypothesis is that nominal stock returns move one-for-one with the rate of inflation so that real stock returns are determined by real factors independently of the rate of inflation. In contrast to the generalized Fisher hypothesis, the empirical evidence finds that common stocks are not a good hedge against inflation. Moreover, real stock returns and inflation are negatively correlated. There exist a number of alternative views as to the explanation of this puzzle. In Chapter 8 we have two objectives. First, to provide an overview of the Fisher hypothesis. Second, to present an extensive literature review that links together the alternative explanations of the stock return-inflation puzzle. This provides the motivation and direction to the following empirical work.

In Chapter 9, we investigate the stock return-inflation puzzle in the context of a simple macroeconomic model involving overlapping wage contracts, as outlined in Chapter 3, which predicts that the negative covariation of real stock returns and inflation is due primarily to aggregate supply side shocks. For quarterly US data, using a multivariate innovation decomposition method we purge the real output and consumer price series of, alternatively, movements over the sample period due to aggregate supply (real productivity) innovations and movements due to aggregate demand (monetary) innovations. The statistical significance of the empirical correlation between the counterfactual inflation series and stock returns is then tested. In addition, we also test other predictions of our simple model concerning the correlation of stock returns and movements in real output due to aggregate demand and supply shocks, as well as the correlation between inflation and real output movements.

Monte Carlo simulations are used to derive counterfactual series for inflation (and real output growth) due to aggregate demand shocks and due to aggregate supply shocks. The simulated counterfactual series are then used to test the relationships between real stock returns and the counterfactual series and in an attempt to explain the inflation-stock return puzzle.

The present value model of stock prices is possibly the most frequently used model to characterize stock price behaviour, in particular in modelling market efficiency. As shown in Chapter 10, the present value model can be presented in either level or loglinear form. In both cases, the present value model implies that real stock prices and dividends are cointegrated. We are interested in the properties of this cointegrating relationship.

Two tests of the present value model are the nonlinear cross-equation restrictions test and the Granger-causality test. The later test is a weak test of the model, and tests whether the price-dividend spread Granger-causes the change in dividends. In contrast, a strong test of the model is the cross-equation restrictions test. A test of the cross-equation restrictions of the present value model is equivalent to a simple Wald test statistic for a regression of asset returns on a lagged information set. Previous empirical work is mixed and is also limited to a linear cointegrating relationship. If the present value model is rejected then it may be misspecified or the discount rate may be nonstationary time-varying. We argue that, due to limits to arbitrage and transaction costs, the relationship between real stock prices and dividends may be non-linear. A detailed discussion of theoretical issues in non-linear testing and modelling the deviations from the long-run equilibrium implied by the present value model is outlined in Chapter 10.

Using quarterly data on real stock prices and dividends for the US we first test the present value model. The results from three tests are reported; these are the cross-equation restrictions, the Granger-causality relationship, and the cointegration between real stock prices and dividends. Second, we test for evidence of non-linear error correction towards the present value model. Third, we parsimoniously model the non-linearity in US real stock prices. The Granger-causality and cointegration tests support the present value model of stock prices. However, the cross-equation restrictions do not hold. The Wald test statistics reject the present value model. Moreover, the evidence reveals that the error correction term should be modelled as a non-linear process. Monte Carlo evidence provides supporting evidence.

Chapter 2

MEAN REVERSION IN STOCK PRICES

2.1 Introduction

The predictability of stock returns is probably the most well-researched topic in the empirical literature on financial economics, dating back at least to Cowles and Jones (1937). Numerous empirical studies have been unable to reject the hypothesis that returns are unpredictable and that stock prices follow a random-walk or martingale process (eg. Granger and Morgenstern, 1963; Fama, 1965, 1970; Le Roy, 1982). This finding supports the efficient market hypothesis. In the last decade, however, various studies have challenged this conventional view and re-examined the predictability of stock returns. Moreover, contrary to the random-walk hypothesis, recent empirical evidence has lent strong support to the hypothesis of mean reversion in stock prices. The influential work of Fama and French (1988a) reports impressive findings that US stock prices are mean reverting (i.e. contain a slowly decaying temporary component) and induce returns characterised by a large negative autocorrelation process for long return horizons, periods of several years. Moreover, Fama and French show that between 25 and 45 percent of the variation of 3 to 5 year US stock returns appears to be predictable from past returns. The Fama and French study has been corroborated by a number of other studies which report similar findings that stock returns contain large predictable components (Poterba and Summers, 1988; Lo and MacKinlay, 1988, 1989; Mills, 1991; Cochran, DeFina and Mills, 1993; Frennberg and Hansson, 1993; Cochrane, 1994; Fraser, 1995; Lee, 1995).[2]

The intuition of the mean-reversion hypothesis is that stock prices contain a transitory component that is mean reverting. Thus, the market value of stocks deviate from their fundamental values but will revert to their mean. The general reason why stock prices deviate from their fundamental value is explained by Keynes (1936) that "all sorts of considerations enter into the market valuation which are in no way relevant to the prospective yield" (p. 152).[3] More specifically, there exists a number of competing theories that explain the deviation of the market and fundamental values, including noise traders (De Long, Shleifer, Summers and Waldmann, 1990), fads (Shiller, 1984) and speculative bubbles (Blanchard and Watson, 1982).

The 'noise trader' literature has received considerable attention as an alternative to the efficient markets paradigm. The noise trader approach assumes that "some investors are not fully rational and their demand for risky assets is affected by their beliefs or sentiments that are not fully justified by fundamental news." Also, "arbitrage - defined as trading by fully rational investors not subject

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[2]Jegadeesh (1991) finds evidence that the empirical evidence of mean reversion in stock prices is due to the January effect. That is, stock prices exhibit seasonal mean reversion in January.

[3]It is interesting to note that John Maynard Keynes (1936), *The General Theory of Employment, Interest and Money*, Chapter 12 (reprinted 1973 version) 'The State of Long-Term Expectation' identified many of the issues that are currently being modelled in finance, for example, speculative bubbles, noise traders, and fads.

to such sentiment - is risky and therefore limited" (Shleifer and Summers, 1990, pp. 19-20). The risk facing arbitrageurs is that equities do not have close substitute portfolios, and therefore if they are priced away from their fundamental, there is no riskless hedge for the arbitrageur. Therefore, the combined demand of a finite number of risk-averse arbitrageurs is not perfectly elastic - that is, there are limits to arbitrage (Shleifer and Vishny, 1997). Furthermore, since stock prices which deviate from fundamentals in a highly persistent way look like they are following a random walk, arbitrageurs would find it difficult to detect such a deviation (Summers, 1986).

Investor sentiment is not irrelevant in causing stock prices to deviate from their fundamentals, and possibly by large amounts. Given that arbitrageurs have short horizons (or at least a finite horizon) they incur a risk in buying a share that has deviated below its fundamental value, since irrational investors (these could also include "trend chasers", "chartists", and "technical analysts") may cause it to fall further. It may pay arbitrageurs to jump on the bandwagon themselves. Therefore, although stock prices may reflect fundamentals in the limit, they may deviate substantially from their fundamentals for long periods of time (De Long *et al.* 1990). "In other words, shifts in the demand for stocks that do not depend on news or fundamental factors are likely to affect prices even in the long run" (Shleifer and Summers, 1990, pp. 25). Therefore, investment success requires not only predicting future fundamentals but also other investors' future trades.[4] The net effect of limits to arbitrage and noise trading leads to a positive autocorrelation of returns at short horizons and a negative autocorrelation of returns at longer horizons - that is, stock prices are mean reverting.

If stock prices are mean reverting then returns must be negatively serially correlated at some frequency. Fama and French (1988a) reports that the frequency at which returns are negatively serially correlated is between 3 and 5 years.[5] The finding that returns are negatively serially correlated at long horizons leaves it open to the criticism that the finding could have arisen from variation in expected returns and variation in risk factors over time. However, expected returns would need to vary a great deal to explain the observed findings. Obviously, the longer the return horizon the higher the potential for expected return and risk factors to change. Thus, evidence of negatively serially correlated returns is only weak evidence against the efficient market hypothesis.[6]

We can investigate the mean-reversion hypothesis using Summers' (1986) simple model for stock prices. Let q_t be the natural logarithm of a stock price at

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[4]In a similar line of reasoning, Keynes (1936) in *The General Theory of Employment, Interest and Money*, (reprinted 1973 version) Chapter 12, p. 156, referred predicting stock prices as picking the winner of a 'beauty contest'.

[5]This finding is supported by other studies (for example, Poterba and Summers, 1988).

[6]Cecchetti, Lam and Mark (1990) demonstrates that negative serial correlation in long horizon stock returns is consistent with an equilibrium model of asset pricing.

time t, is modelled as the sum of a permanent (q^*_t) and transitory (u_t) component. The permanent (or nonstantionary) component, q^*_t, is a random walk and the transitory (or stationary) component, u_t, is any zero-mean stationary process, for example, a first-order autoregression, i.e., a persistent non-random component.[7] Since u_t is stationary, it is mean reverting by definition and reverts to its mean of zero in the long run.

(2.1) $$q_t = q_t^* + u_t$$

(2.2) $$q_t^* = q_{t-1}^* + \mu + \epsilon_t$$

(2.3) $$u_t = \rho u_{t-1} + v_t$$

where μ is the expected drift, ρ is close to but less than unity, and ϵ_t and v_t are white noise and independent errors. A test of the random-walk hypothesis is that ρ is equal to unity. The further away is ρ from unity the greater the degree of persistence of the transitory component. Thus, if ρ is significantly smaller than unity, stock prices are mean reverting - there exists a persistent transitory component and implies predictability (negative autocorrelations) of returns. The above model is used as the theoretical basis for the testing methodologies discussed in the remaining sections of this chapter.

The mean-reversion hypothesis implies that lagged information predicts stock returns. Many recent studies find that stock returns can be predicted by

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[7]That is, positive values of u tend to be followed by further positive values and negative vales followed by negative values.

lagged information, with the predictable component in stock returns related to the business cycle (Fama and French, 1989; Balvers, Cosimano and McDonald, 1990; Breen, Glosten and Jagannathan, 1990; Cochrane, 1991a; McQueen and Roley, 1993). Moreover, Pesaran and Timmermann (1995) show that stock returns are predictable to a magnitude that is economically exploitable and the degree of predictability is not only related to the business cycle but also to the magnitude of the macroeconomic shocks. Thus, Pesaran and Timmermann (1995) reinforce other multivariate studies that stock returns are predictable using a relatively small number of independent variables.

It is noticeable that studies that have tested the mean-reversion hypothesis have tended to concentrate on US stock prices, principally because of the availability of high quality non-overlapping long time series for US stock prices that previous testing techniques requires. With the exception of a few studies (Poterba and Summers, 1988; Cochran, DeFina and Mills, 1993; Frennberg and Hansson, 1993; Mills, 1991, 1995; Cochran and Defina, 1995) markets other than the US have tended to be neglected.

The interest in worldwide investing warrants information on markets other than the stock markets of US, UK and Japan. The results from a range of stock markets provides evidence on the time series properties of stock returns and allow more general inferences than do results on a single country. This is one of the issues that is considered in Chpater 6.

Studies of mean reversion and the associated predictable component of stock prices tend to rely on one of two related testing methodologies: the test of autoregression on multi-period returns - the regression-based test (Fama and French, 1988a) - and the variance-ratio test (Cochrane, 1988; Cochrane and Sbordone, 1988; Poterba and Summers, 1988; Lo and MacKinlay, 1988). More recently, vector autoregressive analysis has also been used to identify the permanent and temporary components of stock prices (eg. Cochrane, 1994; Lee, 1995). The remaining sections of this chapter will critically evaluate and investigate empirical findings of each of these testing methodologies.

2.2 Regression Based Tests

The regression-based test of mean reversion considers the pattern of the autocorrelation function over increasing return horizons. The pattern consistent with mean reversion is positive autocorrelation for low return horizons and negative autocorrelation for longer horizons. Fama and French (1988a) report a U-shaped pattern of the autocorrelation function, which is consistent with evidence of mean reversion.

The negative autocorrelation at longer return horizons can be illustrated using the simple stock price model as outlined in equations (2.1) - (2.3). We can express stock returns, the first difference of the natural logarithm of stock prices, as follows

$$
\begin{aligned}
\text{(2.4)} \qquad r_t = \Delta q_t &= q_t - q_{t-1} \\
&= q_t^* - q_{t-1}^* + [u_t - u_{t-1}] \\
&= \mu + \epsilon_t + [u_t - u_{t-1}]
\end{aligned}
$$

The permanent component produces white noise (with drift) in returns. Whereas, Fama and French (1988a) show that the transitory component causes negative autocorrelation in returns. The autocorrelation function of $[u_t - u_{t-1}]$ is bounded between -0.5 and 0. Consider T-period non-overlapping returns generated by

$$
\begin{aligned}
\text{(2.5)} \qquad r_{t,t+T} &= q_{t+T} - q_t \\
&= q_{t+T}^* - q_t^* + [u_{t+T} - u_t]
\end{aligned}
$$

For any zero-mean stationary process, including an AR(1) process (2.3), the first-order autocorrelation of T-period changes in u_t is given by the slope coefficient (ρ_T) of $[u_{t+T} - u_t]$ on $[u_t - u_{t-T}]$, and approaches -0.5 as T gets larger and 0.0 for small T. Thus a slowly decaying mean-reverting component of stock prices will not be found with short return horizons but are evident in long return horizons.

Although we do not directly observe the transitory component u_t, it is not difficult to show that the theoretical slope in the regression of the return $r_{t,t+T}$ on $r_{t-T,t}$ is 0.0 if the price does not have a transitory component. If the price does not have a random-walk component, for large T, the slope coefficient approaches -0.5. Thus, for large T, the mean-reverting component pushes the first-order autocorrelation of returns to -0.5 and the random-walk component pushes it to 0.0. Since the variance of the random-walk component (σ_ϵ^2) increases proportionally with T, the first-order autocorrelation of returns (that includes random-walk and mean-reverting components) is expected to be close to 0.0 for short return horizons becoming negative for longer return horizon and then, as T gets even larger, moves back towards 0.0 as the random walk component begins to dominate. Thus, a U-shaped pattern of the autocorrelation function is consistent with evidence of mean reversion.

Fama and French (1988a) estimate an autoregression

$$(2.6) \qquad r_{t,t+T} = \alpha + \beta_T r_{t-T,t} + \varepsilon_t$$

for different T-periods return horizons, from one to ten years. The data are 1-month returns for all New York Stock Exchange (NYSE) stocks and are adjusted for inflation using the U.S. Consumer Price Index (CPI) for the 1926-85 period from the Center for Research in Security Prices (CRSP database). Fama and French find a U-shaped pattern across increasing return horizons. The autocorrelations (as measured by the slope coefficient, β_T, in (2.6)) become significantly negative for return horizons between 2 and 7 years - the strongest evidence for 3-5-year returns. The autocorrelations are close to 0.0 for all other years. This pattern is consistent with the hypothesis that stock prices have a mean-reverting component, i.e, a slowly decaying stationary component. The size of the autocorrelation (between −0.30 and −0.45) indicates that, on average, between 60 percent and 90 percent of the variances of 3-5-year returns are due to the transitory component. Moreover, for the same return horizons, the predictable variation due to mean reversion is about 35 percent.

The are a number of additional features of this seminal study. First, the autocorrelations are close to 0.0 for periods after 1940 and the U-shaped pattern for increasing return horizons is not evident (Fama and French, 1988a). Kim, Nelson and Startz (1991) suggest that mean reversion is a feature of the pre-second world war environment but not the post-war environment. Using the regression-based test, Kim *et al.* are unable to predict 3-year ahead returns. The pre-war period incorporates the Great Depression from 1929 to 1939, a period of stock returns unparalleled in the history of the stock market and this may be a contributing factor in the Fama and French (1988a) results.[8] However, as Kim *et*

[8]See Schwert (1990a,b) for a discussion of the importance of the Great Depression period in empirical research.

al. point out, if stock returns are independent, then the serial-correlation patterns in different samples should also be independent.

In an 18 country study, for the 1969:12-1990:10 period, Cochran and DeFina (1995) report only weak support for the mean-reversion hypothesis. Only 2 of the 18 countries (Canada and Norway) exhibit negative serially autcorrelated returns. However, given the small sample size, Cochran and DeFina only consider 3-month to 48-month return horizons. In a study on Swedish stock prices, Frennberg and Hansson (1993) reject the random-walk hypothesis for the 1919-1990 period and also for subperiods.

Second, there is evidence of poor small-sample performance of the test statistics. The small sample arises because even though the sample period may be very large, the number of non-overlapping return observations is necessarily small and therefore there is not much independent information in the return series. Thus, the reliability of inference drawn from individual point estimates of long-horizon autocorrelations has recently been questioned (Richardson and Stock, 1989; Jegadeesh, 1990; Kim *et al.*, 1991; Mankiw, Romer and Shapiro, 1991; Richardson, 1993). The difficulty in drawing inferences from t-statistics based on overlapping data arises because the approximating asymptotic distributions perform poorly. The long-horizon t-statistics tend to overstate the degree of mean reversion. Using an alternative asymptotic distribution theory for statistics involving multi-year returns, Richardson and Stock (1989) and Richardson (1993) show that empirical inference does not easily reject the hypothesis of no mean reversion - the number of significant negative autocorrelations at long return horizons is reduced substantially. Mankiw *et al.* (1991) find only moderate evidence against the random-walk hypothesis. In fact, Cecchetti *et al.* (1990) and Richardson (1993) show that the U-shaped pattern is consistent with stock prices following a random-walk process.

Using randomization methods (as opposed to the Hansen and Hodrick's 1980 method)[9] to calculate bias-adjusted standard errors, Kim *et al.* (1991) find a lower significance of mean reversion in the full sample period. Fama and French (1988a) use the Hansen and Hodrick method in calculating standard errors that adjust for the biased induced by overlapping observations. The advantage of the randomization method is that it does not assume the normality of the underlying returns.

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[9]Using Monte Carlo analysis Hodrick (1992) finds that the Hansen and Hodrick (1980) procedure is biased at long horizons.

2.3 Variance-Ratio Tests

The variance-ratio test, first employed by Cochrane (1988), compares the relative variability of returns over different horizons. Under the null hypothesis of a random walk in stock prices, the variance-ratio test tests whether the ratio of the return variance for a T-period return horizon to a 1-period return horizon is equal to T, as it should be if prices follow a random walk (Cochrane, 1988). Defining, the variance-ratio statistic as

$$(2.7) \qquad \mathrm{VR(T)} = \frac{Var(r_t^T)}{T\,[Var(r_t^1)]}$$

where r_t^T is the T-period return. The null hypothesis of a random walk is rejected if this is statistically different from 1.0. Moreover, if VR(T) is significantly below 1.0, the returns are negatively serially correlated, such as the mean-reversion model. Cochrane (1988) showed that the variance-ratio statistic is approximated by

$$(2.8) \qquad \mathrm{VR(T)} \approx 1 + 2\sum_{j=1}^{T-1}\left[\frac{T-j}{T}\right]\hat{\rho}(j)$$

where $\hat{\rho}(j)$ denotes the j-th-order sample autocorrelation coefficient of the 1-period stock return. For monthly returns, Poterba and Summers (1988) define the variance-ratio statistic as

$$(2.9) \qquad VR(T) = \frac{Var(r_t^T)/T}{Var(r_t^{12})/12}, \qquad r_t^T = \Sigma_{i=0}^{T-1} r_{t-i}$$

$$\approx 1 + 2\sum_{j=1}^{T-1}\left[\frac{T-1}{T}\right]\hat{\rho}(j) - \sum_{j=1}^{11}\left[\frac{12-j}{12}\right]\hat{\rho}(j)$$

where T denotes years and r_t is the return over one month and $\hat{\rho}(j)$ is the j-th-order sample autocorrelation coefficient of monthly stock returns.

Frennberg and Hansson (1993) show that the variance ratio and the slope coefficient in equation (2.6) are directly related. Therefore, it is not surprising that the results from the variance-ratio test provide similar results to that of the regression-based tests. However, the variance-ratio tests are also subject to the same problems as the regression-based tests. First, the results are subject to the problems of inference in small samples. Second, there is no analytically derived distribution for finite samples of the variance ratio - the level of significance depends on how the standard errors are estimated. Third, the empirical finding of mean reversion in stock prices is influenced by the Great Depression period.

In order to estimate the standard errors of the variance ratio, Poterba and Summers (1988) and Lo and MacKinlay (1988, 1989) use Monte-Carlo simulations, assuming normal disturbances. Poterba and Summers (1988) find that returns for the 18 countries in their study are mean reverting for 3 - 8-year return horizons (i.e., the VR(T) is significantly below 1.0 for T between 3 and 8 years). The findings are robust to the sample choice. However, the results are only significant at low significance levels (i.e., at the 0.15 level). The variance ratio point estimates imply that the transitory component explains half of the variance in monthly returns.

The relatively large standard errors, and thus the low power of the test, has resulted in contrasting findings. This is especially the case once alternative methods are employed to estimate the standard errors. More recent studies have suggested that the approach taken by Poterba and Summers (1988) overstates the significance of mean reversion in stock prices. Kim *et al.* (1991) suggest that a more robust approach is to use the randomization method in calculating the standard errors. They find a much lower level of significance than that reported by Poterba and Summers (1988). Richardson and Stock (1989) and Richardson (1993) report a similar finding. A number of other recent studies have tended to support the view that there is only weak evidence for the mean-reversion hypothesis, especially studies that use pre-war data (Frennberg and Hansson, 1993; Cochran and DeFina, 1995).

A related drawback of the variance ratio (and regression-based) testing procedures is that there exist only a relatively few non-overlapping long time series of high quality data available with which to estimate the permanent component of stock prices. Generalization of the results therefore becomes dependent on these few series. Also, the size of the mean-reverting component is sensitive to the choice of index considered. For the New York Stock Exchange (Center for Research in Securities Prices, CRSP, database) the predictability of equally weighted portfolios is substantially higher than for value weighted portfolios (Fama and French, 1988a; Poterba and Summers, 1988; Kim *et al.*, 1991; Mills, 1991, 1995; Cochran and DeFina, 1995).

As in the case of the regression approach, more recent studies using US data suggest that there is only weak support for the mean-reversion hypothesis in the post-war period, and moreover for the last few decades (Richardson and Stock, 1989; Kim *et al.*, 1991; Cochran and DeFina, 1995). Kim *et al.* (1991) find that, for the US, the variance ratio is greater than one (i.e., evidence of mean aversion - positively serially correlated returns) for the pre-war period. Detailed evidence of mean reversion of other countries stock prices is limited, for example, Mills (1991, 1995) report evidence of mean aversion in UK stock prices. Frennberg and Hansson (1993) also find, for Sweden, that stock prices are mean averting for 2-24-month return horizons and the variance ratio falls below one (though never statistically significant) for return horizons greater than 120-months.

In summary, the variance-ratio and the regression-based tests suggest that stock prices are to some degree mean reverting. However, the significance of the mean-reverting component is not certain because of small non-overlapping sample size, the distribution property of the tests and the sensitivity to the pre-war period. It is from this basis that we consider the alternative multivariate testing procedures that have recently been employed.

2.4 Decomposition of Stock Prices: Beveridge-Nelson and Vector Autoregressive Approaches

More recent studies have tended to employ more sophisticated statistical techniques in attempts to ascertain whether stock price movements are mean reverting (e.g. Cochrane and Sbordone, 1988; Cochrane, 1994; Lee, 1995; Mills, 1995). These papers employ a variant of the Beveridge-Nelson (1981) decomposition, with emphasis placed on a multivariate generalization of the decomposition.

The multivariate Beveridge-Nelson (1981) decomposition of stock prices can be expressed using equations (2.1) - (2.3) with an expression for dividends, given by,

$$(2.10) \qquad d_t = q_t^* + w_t$$

where d_t is the natural logarithm of dividends that contains a common random walk component q^*_t (described by equation (2.2)) and a distinct mean zero stationary component, w_t, for example a first-order autoregression. It is not difficult to show that the present value model of stock prices implies a stationary price-dividend ratio, i.e. stock prices and dividends are cointegrated (see Chapter 10). Therefore, taking stock prices and dividends to be cointegrated, there exists a Stock and Watson (1988) common-trends representation in the two-variable vector autoregressive system of stock prices and dividends (Cochrane and Sbordone, 1988). The common-trends component, represented by q^*_t in equations (2.1), (2.2) and (2.10) represents the permanent component in stock prices. The remaining variation in stock prices is due to the transitory (or mean-reverting) component, u_t.

It is in the multivariate context that Cochrane and Sbordone (1988) and Mills (1995) estimate the variance-ratio tests for different return horizons. Cochrane and Sbordone (1988) show that the variance of the permanent or random walk component of stock prices is 1/T times the variance of T differences of dividends.[10] Therefore, the variance ratio test is calculated by dividing 1/T times the variance of T differences of dividends by the variance of the first differences of stock prices. The empirical findings do not strongly support the mean reversion hypothesis, because the standard errors of the pure random walk are considerable larger then the transitory component. For example, Cochrane and Sbordone (1988) findings cannot reject the random walk hypothesis at 5% significance level. For UK stock prices, Mills (1995) finds that the null hypothesis of a random walk cannot be rejected at conventional significance levels when the standard errors are based on Richardson and Stock's (1989) alternative asymptotic theory. However, using the critical values, obtained by Monte Carlo simulation (provided in Mills (1991)), monthly stock prices are mean averting for large return horizons.[11] Like their univariate counterpart, the variance ratios calculated from the multivariate Beveridge-Nelson decomposition do not strongly

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[10]See Cochrane and Sbordone (1988) for a detailed account of decomposing stock prices into transitory and permanent components using a multivariate generalisation of the Beveridge and Nelson (1981) decomposition.

[11]Mills (1995) does not provide a detailed account of the values of either the variance ratios or their standard errors.

reject the random walk hypothesis.

An alternative perspective on the mean-reversion literature is given by Cochrane (1995) and Lee (1995). They argue that univariate estimation of stock prices will not reject the random-walk hypothesis for short autoregressions (for example, AR(1)) and mean reversion is evident in univariate analysis only from long return horizons. However, evidence from mean reversion in stock prices comes when one isolates a transitory *multivariate* shock.

Cochrane (1995) estimate a vector autoregression (VAR) of annual changes in the natural logarithm of stock prices and changes in the natural logarithm of dividends for the 1927-1988 period. Furthermore, since stock prices and dividends are cointegrated the (one period lag of the) natural logarithm of the dividend/price ratio is included in the VAR. Two shocks on stock prices (and dividends)[12] are isolated - a dividend ("permanent") shock causes stock prices to immediately move to their long-run values and a price ("temporary") shock has only a transitory effect on stock prices.[13] Furthermore, the temporary shock is persistent with a half-life of about 5 years. The size of the transitory component

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[12]Dividends are very close to a pure random walk - a dividend (or "permanent") shock explains 99% of the variance in the changes in dividends. This finding is consistent with the hypothesis that mangers smooth dividends by setting dividends equal to the discounted value of earnings (discounted at the risk-free rate).

[13]The present value hypothesis (stationary dividend/price ratio) and the hypothesis that managers smooth dividends (dividends are random walk) define the price shock as completely transitory and the dividend shock as completely permanent.

is large and consistent with the long return horizon analysis - some 57 percent of the variance of returns is explained by temporary shocks.

Employing a less restricted two-variable autoregression involving stock price-dividend spreads and real stock prices, Lee (1995) reports similar results for quarterly data for a slightly longer sample period, 1926:1-1991:4. The distinguishing feature of Lee (1995) is that permanent and temporary shocks to stock prices are identified using the present value hypothesis (i.e., a stationary dividend/price ratio) and dividends to be some non-stationary, I(1) process. Unlike Cochrane (1995), who assumes that the dividend series is a random walk, Lee (1995) models dividends that include both a random walk and a stationary component.[14] It is this definition of dividends that allows Lee (1995) to estimate a variant of the decomposition technique proposed by Blanchard and Quah (1989).

Lee (1995) also faces the cointegration problem identified by the present value model (Campbell and Shiller, 1987). The stock price and dividend series are both integrated of the order 1, I(1). However, a VAR of the first difference of stock prices and dividends is not viable since the moving average representation of the vector is noninvertible (Engle and Granger, 1987).

[14]Empirically, dividends may either be a random walk or also include a stationary component. Annual data looks like a random walk whereas this is less certain for quarterly data. Therefore, econometrically both authors are valid in their approach.

Defining the cointegration residual as the 'spread' between stock prices and dividends,[15] Lee (1995) estimates a restricted bivariate VAR of the price-dividend spread and stock returns and identifies the temporary and permanent shocks to stock prices by restricting the long-run response of the temporary shock to stock prices to equal zero. The permanent and temporary shocks are attributed to the dividend series - the random walk component generates the permanent innovations (shocks) and the stationary component generates the temporary innovations. The two dividend innovations are related to stock prices through the present value model.[16]

These recent studies strongly support the mean-reversion hypothesis and suggest a large mean-reverting component, around 50-60 percent, in US (and international) stock prices, at least for studies that include the pre-war period. Cochrane (1995) finds that the dividend/price ratio forecasts stock returns more strongly in the postwar than in the data series that includes prewar data.

The temporary component characterised by the vector autoregression approach can be thought of as a long-horizon forecastability test. It is this feature that makes it particularly appealing in identifying mean reversion in stock prices, in that predictability requires a long investment horizon.

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[15]When stock prices and dividends are expressed as natural logarithms, the spread is defined as the log of stock prices minus the log of dividends.

[16]As identified by Cochrane (1995), the dividend/price ratio helps predict stock returns (see also, Fama and French, 1988a; Campbell and Shiller, 1988, 1989; Hodrick, 1992; Cochran, DeFina and Mills, 1993).

Evidence of a large mean-reverting component implies that stock returns are predictable for long investment horizons. The view that stock prices are predictable has resulted in numerous recent studies supporting the predictability of stock returns (eg. Fama and French, 1989; Mills, 1991, 1993a; Cochrane and Mansur, 1993; Black and Fraser, 1995; Fraser, 1995; Pesaran and Timmermann, 1995).[17] The majority of these studies have examined the dividend/price ratio as a forecasting factor of stock returns, however, a small number of studies have considered aggregate business factors (for example, Fama and French, 1989; Cheung and Lai, 1995; Pesaran and Timmermann, 1995).

[17]In turn, this has important implications for the use of models that assume that stock returns are unpredictable, such as the present value model of stock prices.

Chapter 3

A SIMPLE MACRO MODEL

3.1 A Simple Macro Model with Overlapping Wage Contracts

In this section we have two objectives. First, using a simple macro model with overlapping nominal wage contracts, we demonstrate that changes in real stock prices may be serially correlated even under the assumption of fully efficient markets in the sense that there are no profitable arbitrage opportunities between current and expected stock price movements. Second, in the context of the same macro model, we show that aggregate demand shocks have only temporary effects on real stock prices, while supply shocks may affect the level of real stock prices permanently.

In the traditional ADAS model with a long-run vertical supply curve, aggregate demand innovations result in only a temporary rise in output, while aggregate supply innovations permanently affect the level of aggregate output. That is, in the long run, aggregate-demand innovations raise the price level but not output. It is in this context that we outline the model below.

Consider a simple loglinear macro model with overlapping nominal wage contracts which is essentially neoclassical and Fisherian in structure - and which allows reasonably complex dynamics.[18] In order to illustrate the relationship

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[18] A characteristic feature of the model is that wages are set in a two-period overlapping contracts framework.

between macroeconomic and financial time series the model includes a stock price determination equation. The model incorporates the salient features of the models of Fischer (1977), Blanchard (1981) and Blanchard and Quah (1989):

$$(3.1) \quad y_t = m_t - p_t + a\theta_t + \alpha\pi_t$$

$$(3.2) \quad y_t = n_t + \theta_t$$

$$(3.3) \quad p_t = w_t - \theta_t$$

$$(3.4) \quad w_t = w|\{E_{t-2}n_t = \bar{n}\}$$

$$(3.5) \quad \pi_t = \phi y_t$$

$$(3.6) \quad q_t = \pi_t + \sum_{j=0}^{\infty} \rho^j E_t \Delta\pi_{t+1+j} + k^*$$

where the permissible range of the parameter space is governed by:

$$(3.7) \qquad a > 0, \quad 0 < \alpha < 1, \quad 0 < \phi < 1, \quad 0 < \rho \leq 1$$

The variables, y, m, p, w, n, and θ denote, respectively, the log of output, the money supply, the price level, the nominal wage, employment and productivity, respectively. The log of dividends on equities is represented by π; $\bar{n}$ represents full employment; and q is the log of the real price of equities.

Equation (3.1) represents the aggregate demand side of the economy; with aggregate demand a function of real balances, productivity and distributed profits. For generality, we follow Blanchard and Quah (1989) in allowing productivity to affect aggregate demand on the grounds that it is likely to affect investment, so that we expect a>0, although setting a=0 does not qualitatively alter the results. The production function, equation (3.2), relates output to the level of employment and productivity. Equation (3.3) states that the price level is a function of the nominal wage and productivity. The nominal wage (equation (3.4)), chosen two periods ahead, is set at the expected full employment level in a two-period overlapping contracts framework (Fischer, 1977). Equation (3.5) expresses log of real dividends (distributed profit) as a function of real output.

Equation (3.6) specifies the log of real stock prices as a linear function of the log of real dividends. Following Campbell and Shiller (1988a,b), the log of real stock prices is a log-linear approximation of the standard present value model of stock prices.[19] The equation says that the log real stock price at time t is determined by the log real dividend at time t, expected real dividend growth into the infinite future, and a constant. Future real dividend growth rates are discounted at the rate ρ^j, for $j=0,..,\infty$, where ρ is close to but a little smaller than (positive) unity. A detailed derivation of equation (3.6) is given at the end of this chapter in Appendix 3.1.

To close the model, we follow Blanchard and Quah (1989) in assuming that m and θ are determined as follows:

(3.8) $$\theta_t = \theta_{t-1} + e_{s,t}$$

(3.9) $$m_t = m_{t-1} + e_{d,t}$$

where e_d and e_s are serially uncorrelated and pairwise orthogonal demand and

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[19]We assume the dividend enter the log dividend-price ratio, $\delta_t \equiv \pi_t - q_t$, in the current period t, that is, the dividend in period t is also known in period t.

supply disturbances.

We solve the above model for the variables of interest (Δp_t, Δq_t, and Δy_t) in terms of the two disturbances ($e_{d,t}$ and $e_{s,t}$). The approach taken is first to calculate an expression for real output growth. Second, given the role of real output in the stock price formation equation we use the expression for real output growth to find real stock returns in terms of supply and demand disturbances. Finally, we calculate an expression for inflation in terms of two disturbances.

From (3.1) and (3.5):

$$(3.10) \quad y_t = (1-\alpha\phi)^{-1}(m_t - p_t + a\theta_t)$$

Substituting (3.3) into (3.10) and taking expectations in period t−2:

$$(3.11) \quad E_{t-2}y_t = (1-\alpha\phi)^{-1}(m_{t-2} - w_t + (1+a)\theta_{t-2})$$

Also, taking expectations of (3.2) in period t−2, gives:

$$(3.12) \quad E_{t-2}y_t = \bar{n} + \theta_{t-2}$$

Equating (3.11) and (3.12), we derive an expression for full employment:

$$(3.13) \quad \bar{n} = (1-\alpha\phi)^{-1}(m_{t-2} - w_t + (1+a)\theta_{t-2}) - \theta_{t-2}$$

From (3.2), (3.3) and (3.10):

$$(3.14) \quad n_t = (1-\alpha\phi)^{-1}(m_t - w_t + (1+a)\theta_t) - \theta_t$$

Subtracting (3.14) from (3.13) we calculate an expression for the gap between actual and full employment:

$$(3.15) \quad \bar{n} - n_t = -(1-\alpha\phi)^{-1}(m_t - m_{t-2}) \\ - (1-\alpha\phi)^{-1}(1+a)(\theta_t - \theta_{t-2}) + (\theta_t - \theta_{t-2})$$

We can rewrite (3.15) in terms of the supply and demand disturbances using (3.8) and (3.9):

$$(3.16) \quad \bar{n} - n_t = -(1-\alpha\phi)^{-1}(e_{d,t} + e_{d,t-1}) \\ - (1-\alpha\phi)^{-1}(1+a)(e_{s,t} + e_{s,t-1}) + (e_{s,t} + e_{s,t-1})$$

Given that:

$$(3.17) \quad \Delta n_t = -\Delta(\bar{n} - n_t)$$

we can calculate the change in employment by combining (3.16) and (3.17):

$$(3.18) \quad \Delta n_t = (1-\alpha\phi)^{-1}(e_{d,t} - e_{d,t-2}) \\ + (1-\alpha\phi)^{-1}(1+a)(e_{s,t} - e_{s,t-2}) - \Delta e_{s,t} - \Delta e_{s,t-1}$$

Taking the first difference of (3.2):

$$(3.19) \quad \Delta y_t = \Delta n_t + \Delta\theta_t$$

Substitute (3.8) into (3.19) and combine the resulting expression into (3.18) we solve for real output growth in terms of the two disturbances:

$$\Delta y_t = (1-\alpha\phi)^{-1}(e_{d,t} - e_{d,t-2})$$
$$+ (1-\alpha\phi)^{-1}(1+a)(e_{s,t} - e_{s,t-2})$$
$$- \Delta e_{s,t} - \Delta e_{s,t-1} + e_{s,t}$$

Collecting terms:

$$(3.20) \quad \Delta y_t = (1-\alpha\phi)^{-1}(e_{d,t} - e_{d,t-2})$$
$$+ (1-\alpha\phi)^{-1}(1+a)(e_{s,t} - e_{s,t-2}) + e_{s,t-2}$$

Equation (3.20) expresses real output growth in terms of supply and demand disturbances. Demand disturbances have short-run (temporary) effects on real output and these effects disappear over time. In this overlapping wage contracts model, a demand disturbance has no long-run (permanent) effects after two periods. In contrast, supply disturbances have both short-run and long-run effects on real output.

We interpret (3.20) using the parameter space (3.7). Demand disturbances increases real output in the short run and, in the long run real output declines back to its original level. A supply disturbance increases real output in the short run and declines by a fraction of this increase in the long run. Thus, in the long run, the net effect of a supply disturbance is that real output has increased.

We now turn our attention to real stock returns. Substituting (3.5) into (3.6) gives

$$(3.21) \quad q_t = \pi_t + \sum_{j=0}^{\infty} \rho^j E_t \phi \Delta y_{t+1+j} + k^*$$

Since real output growth is given by

$$\Delta y_t = (1-\alpha\phi)^{-1}(e_{d,t} - e_{d,t-2}) + (1-\alpha\phi)^{-1}(1+a)(e_{s,t} - e_{s,t-2}) + e_{s,t-2}$$

Real output growth next period is therefore,

$$\Delta y_{t+1} = (1-\alpha\phi)^{-1}(e_{d,t+1} - e_{d,t-1}) + (1-\alpha\phi)^{-1}(1+a)(e_{s,t+1} - e_{s,t-1}) + e_{s,t-1}$$

and for period t+2,

$$\Delta y_{t+2} = (1-\alpha\phi)^{-1}(e_{d,t+2} - e_{d,t}) + (1-\alpha\phi)^{-1}(1+a)(e_{s,t+2} - e_{s,t}) + e_{s,t}$$

Taking expectations

$$E_t \Delta y_{t+1} = (1-\alpha\phi)^{-1}(-e_{d,t-1}) + (1-\alpha\phi)^{-1}(1+a)(-e_{s,t-1}) + e_{s,t-1}$$

$$E_t \Delta y_{t+2} = (1-\alpha\phi)^{-1}(-e_{d,t}) + (1-\alpha\phi)^{-1}(1+a)(-e_{s,t}) + e_{s,t}$$

$$E_t \Delta y_{t+j} = 0, \qquad \text{for } j > 2$$

Rewrite (3.21) as:

$$(3.22) \quad q_t = \pi_t + k^* + \phi E_t \Delta y_{t+1} + \phi\rho E_t \Delta y_{t+2} + \phi\rho^2 E_t \Delta y_{t+3} + \cdots\cdots$$

Given $E_t \Delta y_{t+i}$, for all i, as above, we can rewrite (3.22) as

$$\begin{aligned}(3.23) \quad q_t = \pi_t &+ \phi[(1-\alpha\phi)^{-1}(-e_{d,t-1}) \\ &\quad + (1-\alpha\phi)^{-1}(1+a)(-e_{s,t-1}) + e_{s,t-1}] \\ &+ \phi\rho[(1-\alpha\phi)^{-1}(-e_{d,t}) \\ &\quad + (1-\alpha\phi)^{-1}(1+a)(-e_{s,t}) + e_{s,t}] + k^*\end{aligned}$$

Taking first difference of (3.23):

$$\begin{aligned}(3.23) \quad \Delta q_t = \phi\Delta y_t &+ \phi[(1-\alpha\phi)^{-1}(-e_{d,t-1} + e_{d,t-2}) \\ &\quad + (1-\alpha\phi)^{-1}(1+a)(-e_{s,t-1} + e_{s,t-2}) \\ &\quad + (e_{s,t-1} - e_{s,t-2})] \\ &+ \phi\rho[(1-\alpha\phi)^{-1}(-e_{d,t} + e_{d,t-1}) \\ &\quad + (1-\alpha\phi)^{-1}(1+a)(-e_{s,t} + e_{s,t-1}) \\ &\quad + (e_{s,t} - e_{s,t-1})]\end{aligned}$$

Substitute equation (3.20) into (3.23) gives us an expression for real stock returns

$$\begin{aligned}(3.24) \quad \Delta q_t = \phi(1-\rho)(1-\alpha\phi)^{-1}&[(e_{d,t} - e_{d,t-1}) \\ &+ (1+a)(e_{s,t} - e_{s,t-1})] \\ &+ \phi\rho(e_{s,t} - e_{s,t-1}) + \phi e_{s,t-1}\end{aligned}$$

Equation (3.24) expresses real stock returns in terms of supply and demand disturbances. Demand disturbances have short-run effects on real stock prices and these effects disappear over time. In this overlapping wage contracts model, a demand disturbance has no long-run effects after one periods. The long-run effect of a demand disturbances has a zero long-run effect on stock prices and real output, however, real stock prices adjust quicker than real output to this long-run position. As in the case of real output, supply disturbances have both short-run and long-run effects on real stock prices.

Given the parameter space (3.7), a demand disturbances increases real stock prices in the short run and, in the long run, real stock prices decline back to their original level. A supply disturbance increases real stock prices in the short run and declines by a fraction of this increase in the long run. As in the case of real output, the net long-run effect of a supply disturbance is an increase in real stock prices.

Finally, we derive an expression for inflation. From (3.1) and (3.5):

$$(3.25) \quad p_t = m_t - (1-\alpha\phi)y_t + a\theta_t$$

Substituting (3.8) and (3.9) into (3.25) gives:

$$(3.26) \quad \Delta p_t = e_{d,t} - (1-\alpha\phi)\Delta y_t + a e_{s,t}$$

Substituting the real output equation (3.20) into (3.26) gives us an expression for inflation:

$$(3.27) \quad \Delta p_t = e_{d,t} - e_{d,t} + e_{d,t-2} - (1+a)(e_{s,t} - e_{s,t-2}) - (1-\alpha\phi)e_{s,t-2} + ae_{s,t}$$

Collecting terms:

$$(3.28) \quad \Delta p_t = e_{d,t-2} - e_{s,t} + (a+\alpha\phi)e_{s,t-2}$$

Equation (3.28) expresses inflation in terms of supply and demand disturbances. Demand and supply disturbances have both short-run and long-run effects on prices. We interpret (3.28) using the parameter space (3.7). A supply disturbance decreases prices in the short run. However, in the long run, the net effect of a supply disturbance depends on the value of $(a+\alpha\phi)$. If $(a+\alpha\phi)>1$, a supply disturbances will increase prices in the long run, whereas, with $(a+\alpha\phi)<1$, prices will decrease in the long run. This is because supply shocks through their effect on investment, may raise aggregate demand (equation (3.1)). If this effect is weak (a is small), the traditional supply-side effects will dominate and a supply shock will depress prices in the long run.

In summary, demand and supply shocks have both short-run and long-run effects on inflation. However, demand shocks have short-run effects on real stock prices and these effects disappear over time. In contrast, supply shocks have both short-run and long-run effects on real stock prices. Equation (3.24) demonstrates that changes in real stock prices may be serially correlated even under the assumption that there are no profitable arbitrage opportunities between current and expected stock price movements - that is, fully efficient markets.

This simple model is consistent with the comparative statics of a standard aggregate supply-aggregate demand framework with a long-run vertical supply curve (ASAD-LRVS)[20]. Aggregate supply innovations increase real output - in both the short and long run - and depress consumer prices, while demand innovations raise prices but can only raise real output in the short run. Furthermore, in our model stock returns are positively related to output, and it is this relationship that explains the negative correlation between inflation and stock returns to aggregate supply shocks.

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[20]See e.g. Gordon, 1978, chapter 7; Branson, 1979, chapter 7; and Cuthbertson and Taylor, 1987, chapter 3.

3.2 Monte Carlo Simulations

This section considers the simple linear macro model with overlapping nominal wage contracts outlined in the previous section. We modify the model by allowing a drift term to enter into the money supply and productivity equations:

$$(3.29) \qquad \theta_t = \theta_{t-1} + \mu_\theta + e_{s,t}$$

$$(3.30) \qquad m_t = m_{t-1} + \mu_m + e_{d,t}$$

where μ_θ and μ_m are the expected drift in the level of productivity and money supply.

In order to run the Monte Carlo simulations we solve the model for the variables of interest (Δp_t, Δq_t, and Δy_t) in terms of the two random serially uncorrelated and pairwise orthogonal demand and supply disturbances ($e_{d,t}$ and $e_{s,t}$). The approach taken is first to calculate an expression for real output growth. Replacing (2.8) and (3.9) by (3.29) and (3.30) in the model, as described by equations (3.1)-(3.7), does not substantially change the expression for Δp_t, Δq_t, and Δy_t. We therefore only provide a brief version of the calculations.

First, solving for real output growth. Taking the first difference of equation (3.2) and substituting (3.29) into the derived equation:

$$(3.31) \qquad \Delta y_t = \Delta n_t + \mu_\theta + e_{s,t}$$

Substituting (3.18) into (3.31) solves for real output growth in terms of the two disturbances:

$$(3.32) \quad \Delta y_t = (1-\alpha\phi)^{-1}(e_{d,t} - e_{d,t-2}) + (1-\alpha\phi)^{-1}(1+a)(e_{s,t} - e_{s,t-2}) + e_{s,t-2} + \mu_\theta$$

Equation (3.32) is analogous to (3.20). Introducing an expected drift term into the money supply and productivity equations, causes only the expected drift in productivity to enter into the real output growth equation.

Second, we solve for the stock return equation. Substituting (3.32) into the first difference of equation (3.5) gives:

$$(3.33) \quad \Delta\pi_t = \phi(1-\alpha\phi)^{-1}(e_{d,t} - e_{d,t-2}) + \phi(1-\alpha\phi)^{-1}(1+a)(e_{s,t} - e_{s,t-2}) + \phi e_{s,t-2} + \phi\mu_\theta$$

Substituting equation (3.33) into equation (3.6), the price of stocks is given by,

$$\begin{aligned}(3.34) \quad q_t = \pi_t &+ \phi[(1-\alpha\phi)^{-1}(-e_{d,t-1}) + (1-\alpha\phi)^{-1}(1+a)(-e_{s,t-1}) + e_{s,t-1}] \\ &+ \phi\rho[(1-\alpha\phi)^{-1}(-e_{d,t}) + (1-\alpha\phi)^{-1}(1+a)(-e_{s,t}) + e_{s,t}] \\ &+ \phi(1+\rho)\mu_\theta + k^*\end{aligned}$$

Taking first difference of (3.34), and substituting (3.33) into the resulting expression, gives us an expression for real stock returns:

$$(3.35) \quad \Delta q_t = \phi(1-\rho)(1-\alpha\phi)^{-1}[(e_{d,t} - e_{d,t-1}) + (1+a)(e_{s,t} - e_{s,t-1})] + \phi\rho(e_{s,t} - e_{s,t-1}) + \phi e_{s,t-1} + \phi\mu_\theta$$

Equation (3.35) is analogous to (3.24). Again, introducing an expected drift term into the money supply and productivity equations, causes only the expected drift in productivity to enter into the real stock return equation, with a coefficient value of ϕ, where $0<\phi<1$.

Third, we solve for inflation. Substituting (3.5) into (3.1) and taking the first difference:

$$(3.36) \quad \Delta p_t = \Delta m_t - (1-\alpha\phi)\Delta y_t + a\Delta\theta_t$$

Substituting (3.29) and (3.30) into (3.36) gives:

$$(3.37) \quad \Delta p_t = e_{d,t} - (1-\alpha\phi)\Delta y_t + ae_{s,t} + \mu_m + a\mu_\theta$$

Substituting the real output growth equation (3.32) into (3.37) gives us an expression for inflation:

$$(3.38) \quad \Delta p_t = e_{d,t-2} - e_{s,t} + (a+\alpha\phi)e_{s,t-2} + \mu_m + (a+\alpha\phi-1)\mu_\theta$$

Equation (3.38) is analogous to (3.28). Both the expected drift terms enter into the price equation. The expected drift in productivity to enter into the price equation, with a negative coefficient value, $(a+\alpha\phi-1)<0$.

We simulate the three equation model for real output growth, stock returns and inflation, given by equations (3.32), (3.35) and (3.38), respectively. To identify the model we assign values to the model's parameters: α=0.1, a=0.4, μ_θ=5.0, μ_m=8.0, ϕ=0.6, and ρ=0.96. Assigning different values to the parameters (within the parameter space given by (3.7)) does not change the qualitative findings. The value of ρ is taken from Campbell, Lo and MacKinlay (1997) to be 0.96 in annual data.

A sample of 100 is replicated 200 times. We exploit the generated inflation, real stock return and real output growth series to examine the importance of the demand and supply shocks in explaining movements in real stock prices.

The R^2s from the regression of real stock returns onto demand, supply and deterministic (constant and trend) components are reported in Table 3.1. Real stock price movements are primarily explained by supply (permanent) shocks, with only 4 percent of the real stock returns explained by demand (temporary) shocks. The 5%- and 95%-iles reveal that even though we are considering normally distributed pure random shocks - that is, no asymmetries such as bubbles - demand (temporary) shocks, at the 95%-ile, explained up to 17 percent of the variation in real stock price movements.

The impulse response functions from demand and supply shocks to real stock prices and to consumer prices are presented in Figure 3.1. The three response functions for each shock is for illustrative purposes. The median response function corresponds to the seed that generates the median value of the initial impulse response of a one unit (standard deviation) demand shock to real stock prices, the low reponse function corresponds to the seed that generates the 5%-ile and the high to the 95%-ile value. A demand shock increases real stock prices only in the short run - prices revert back to the original value in the long run. Whereas, a supply shock increases real stock prices in the short run and long run. In contrast, a supply shock decreases consumer prices in the short run and long run, and a demand shock increases consumer prices. The effect of demand and supply shocks are as predicted by the ASAD-LRVS model.

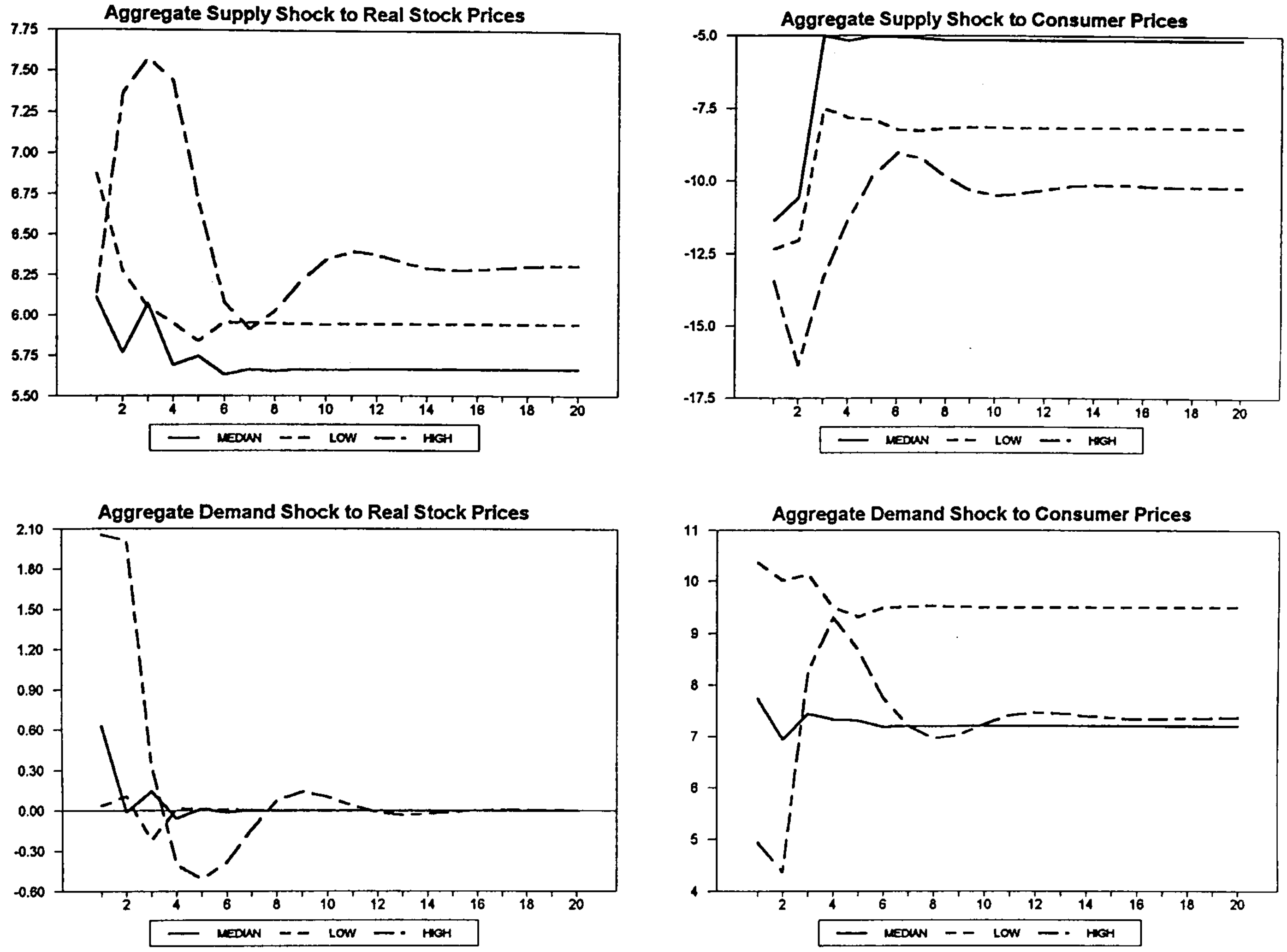
We also use the simulated model in Chapter 9, section 9.1 to examine the inflation-stock return puzzle by examining the correlation between real stock returns, inflation and real output growth. Briefly, the relationship between inflation, real stock returns and real output growth are as expected: inflation due to demand shocks is positively correlated with real output growth due to demand shocks and inflation due to supply shocks is negatively correlated with real output growth due to supply shocks.

Table 3.1: The Percentage of Real Stock Price Movements Explained by Each Component - The Distribution of R^2

	Median	5%-ile	95%-ile
Demand	0.04	0.00	0.17
Supply	0.95	0.82	0.99
Deterministic	0.01	0.00	0.04

Notes: The values are the R^2s from the regression real stock returns onto demand, supply, and deterministic components. The sample size is 100. The table reports both the median value and the 5% upper and lower %-ile values from 200 simulations of the macro model.

Figure 3.1: Cumulative Impulse Response Functions



Appendix 3.1: Derivation of the Real Stock Price Equation (3.6) - A Loglinear Approximation of the Present-Value Relationship.

The appendix draws on Campbell and Shiller (1988a,b) , Campbell (1991), Chapter 7 of Campbell, Lo and MacKinlay (1997) and Cuthbertson Hayes and Nitzsche (1997). We derive an equation for the log of real stock price using a variant of the dividend-ratio model proposed by Campbell and Shiller (1988a,b). The loglinear framework is tractable under the assumption that dividends and returns follow loglinear processes.

The variables used are defined as follows:

$h_{1,t+1}$ = one-period log stock gross return, from time t to time t+1

Q_t = real stock price level in period t

q_t = log real stock price in period t

Π_t = real dividend level in period t

π_t = log real dividend in period t

δ_t = log dividend-price ratio in period t

$\xi_{1,t+1}$ = first-order Taylor approximation of $h_{1,t+1}$

ρ = constant equal to $1/(1+\exp(\delta))$

δ = average log dividend-price ratio

k = constant equal to $-\log(\rho)-(1-\rho)\log(1/\rho-1)$

r = constant equal to the expected real one-period stock returns

The realised one-period, from time t to time t+1, log real stock return, $h_{1,t+1}$, is defined as[21]

$$h_{1,t+1} \equiv q_{t+1} - q_t + \log\left(1 + \exp(\pi_{t+1} - q_{t+1})\right) \tag{A3.1}$$

Thus, the exact relationship between these variables is nonlinear - that is, $\log(1+\exp(\pi_{t+1}-q_{t+1}))$ is a nonlinear function of the log dividend-price ratio, $\delta_{t+1}=\pi_{t+1}-q_{t+1}$. A first-order Taylor approximation around the mean of the log dividend-price ratio, $\delta=\pi-q$, gives

$$\begin{aligned} &h_{1,t+1} \approx \xi_{1,t+1} \\ &\xi_{1,t+1} \equiv k + \rho q_{t+1} + (1-\rho)\pi_{t+1} - q_t \end{aligned} \tag{A3.2}$$

where ρ and k are parameters of linearisation defined by $\rho=1/(1+\exp(\delta))$, where $\delta=\pi-q$ is the average log dividend-price ratio, and $k\equiv-\log(\rho)-(1-\rho)\log(1/\rho-1)$. The parameter ρ is close to but a little smaller than unity. The variable $\xi_{1,\,t+1}$ approximates $h_{1,\,t+1}$ and is linear in the log dividend-price ratios δ_t and δ_{t+1} and $\Delta\pi_{t+1}$:

$$\xi_{1,t+1} = k - \rho\delta_{t+1} + \delta_t + \Delta\pi_{t+1} \tag{A3.3}$$

The higher-order terms in the Taylor expansion are not included, however, Campbell and Shiller (1988b) show that in practice the approximation error is

[21]In linear form, $h_{1,\,t+1} \equiv \log((Q_{t+1} + \Pi_{t+1})/Q_t)$.

small and (more importantly) almost constant.[22]

From (A3.3), we define the discounted i-period return $\xi_{i,\,t+1}$ as:

$$\text{(A3.4)} \qquad \xi_{i,t+1} \equiv \sum_{j=0}^{i-1} \rho^j \xi_{1,t+1+j}$$

The variable $\xi_{i,\,t+1}$ is the discounted sum of approximate returns from t+1 to t+i. From equations (A3.3) and (A3.4) we can rewrite (A3.4) as a linear function of δ_t, δ_{t+i}, and $\Delta\pi_{t+j+1}$, j=0,..., i-1.

$$\text{(A3.5)} \qquad \xi_{i,t+1} = \delta_t - \rho^i \delta_{t+i} + \sum_{j=0}^{i-1} \rho^j \Delta\pi_{t+1+j} + k(1-\rho^i)/(1-\rho)$$

Suppose that expected real one-period stock returns are constant: $E_t\xi_{1,t} = E_t\xi_{1,t+1} = r$.[23] Then taking conditional expectations of the left and right-hand sides of (A3.5) and rearranging, gives an expression for the log dividend-price ratio at time t

$$\text{(A3.6)} \qquad \delta_t = -\sum_{j=0}^{i-1} \rho^j E_t \Delta\pi_{t+1+j} + \rho^i E_t \delta_{t+i} + (r-k)(1-\rho^i)/(1-\rho)$$

[22]When the dividend-price ratio is constant then $\rho = 1/(1+\Pi/Q)$, the reciprocal of one plus the dividend-price ratio, and the approximation holds exactly. The average dividend-price ratio has been about 4% annually, for US data, over the 1926-94 period, implying that ρ should be about 0.96 in annual data, or about 0.997 in monthly data (Campbell *et al.*, 1997).

[23]In practice r is the real return on commercial paper.

where $E_t\xi_{i,t+1}=r(1-\rho^i)/(1-\rho)$. This equation[24] says that the log dividend-price ratio at time t is determined by expectations of future real dividend growth over i periods, by the i-period-ahead expected dividend-price ratio, and by the constant required return on stock. An increase in expected future real dividend growth decreases the current log dividend-price ratio. To consider the log real price of stocks we take the limit as i increases, and assuming that $\lim_{i\to\infty}\rho^i E_t\delta_{t+i}=0$, we have

$$\text{(A3.7)} \qquad \delta_t = -\sum_{j=0}^{\infty} \rho^j E_t \Delta\pi_{t+1+j} + (r-k)/(1-\rho)$$

This equation expresses the log dividend-price ratio as a linear function of expected real dividend growth into the infinite future. Finally, we can expresses (A3.7) as a real stock prices equation:

$$\text{(A3.8)} \qquad q_t = \pi_t + \sum_{j=0}^{\infty} \rho^j E_t \Delta\pi_{t+1+j} + k^*$$

where, $k^*=(r-k)/(1-\rho)$ is a constant. The log real stock price at time t is determined by the log real dividend at time t, expected real dividend growth into the infinite future, and a constant k^*.

---

[24]Equation (A3.6) can be used to derive the so-called "dividend-ratio model" or the dynamic Gordon model, after the original Gordon (1962) growth model. The dynamic Gordon model specifies the loglinear relationship between dividend-price ratio and expected future discount rates and dividends (Campbell and Shiller, 1988b).

Chapter 4

ECONOMETRIC TECHNIQUES: DECOMPOSITION AND ROBUST ESTIMATION

4.1 VAR Decomposition

Blanchard and Quah (1989) suggest an econometric technique to decompose a series into its temporary and permanent components. One advantage of the Blanchard-Quah decomposition is that it identifies permanent and temporary shocks in a multivariate time series context.[25] A number of recent studies have applied the Blanchard-Quah decomposition to macroeconomic and financial variables (Gali, 1992; Gamber and Joutz, 1993; Bayoumi and Eichengreen, 1994; Bayoumi and Taylor, 1995; Lee, 1995; Gamber, 1996).[26] For this reason only a brief outline of the theoretical underpinnings of the decomposition is presented. The fundamental feature of the Blanchard-Quah technique is that it imposes a long-run restriction (making use of economic theory) on the VAR to identify the decomposition.

Consider a 2×1 vector of time series $x_t = [(1-L)x_{1,t}\ \ (1-L)x_{2,t}]'$, where L is the lag operator. Both $(1-L)x_{1,t}$ and $(1-L)x_{2,t}$ are assumed to be realizations at time t from a stationary stochastic process with its deterministic components

[25] Beveridge and Nelson (1981) provide a univariate representation of identifying permanent and temporary shocks.

[26] The econometric method has also been discussed by Quah (1990, 1992, 1995), Blanchard and Quah (1993), Lippi and Reichlin (1993, 1994), Crowder (1995), and Taylor (1996).

removed. The variables $x_{1,t}$ and $x_{2,t}$ are thus assumed to be realizations of first-difference stationary or I(1) processes. By the multivariate form of Wold's decomposition x_t will have a moving average representation. However, Engle and Granger (1987) demonstrates that if x_t is cointegrated[27] of order 1, 1, $x_t \sim CI(1,1)$ then the vector of Δx_t is not well behaved, in that the moving average representation of that vector is noninvertible. Therefore, a necessary condition for the Blanchard-Quah (1989) decomposition is that the vector x_t is not cointegrated - for example, this prohibits estimating a vector of first differenced stock prices and dividends using the Blanchard-Quah technique. If x_t is a cointegrating vector then an alternative decomposition technique is the Stock and Watson (1988) common trends representation. Cochrane (1994) examines the relationship between the Sims (1980), Blanchard-Quah (1989), and Beveridge-Nelson (1981) decompositions and cointegration and Crowder (1995) examines the relationship between the Blanchard-Quah decomposition, the Stock and Watson (1988) common trends representation and cointegration.

We will concern ourselves with non-cointegrating vectors. Consider a transformation of the Wold representation given by:

[27]That is, $x_{1,t}$ and $x_{2,t}$ are integrated of the order 1 (i.e., stationary in first differences) and there exists a vector $\beta(\neq 0)$ where $\beta' x_t$ is integrated of order 0 (i.e., stationary).

$$(4.1) \qquad x_t = \sum_{j=0}^{\infty} L^j \begin{bmatrix} a_{11}(j) & a_{12}(j) \\ a_{21}(j) & a_{22}(j) \end{bmatrix} \begin{bmatrix} e_{T,t} \\ e_{P,t} \end{bmatrix}$$

$$= \sum_{j=0}^{\infty} L^j A(j) e_t$$

where e_t is a 2×1 vector of innovations $[e_{T,t} \;\; e_{P,t}]'$ occurring at time t and $a_{mn}(j)$ (m,n=1,2) represents the impulse response of the m-th element of x_t to the n-th element of e_t after j periods.

By imposing restrictions on the coefficients of (4.1) and on the covariance matrix of the innovations, the elements of e_t can be identified as temporary (e_T) and permanent (e_P) innovations to x_1. By assumption, x_2 is affected by the same two innovations, although a permanent or temporary innovation to x_1 need not necessarily affect x_2 in the same way.

For a temporary innovation to x_1, the cumulative effect of the shock on changes in x_1 are zero. This implies the restriction

$$(4.2) \qquad \sum_{j=0}^{\infty} a_{11}(j) = 0$$

Suppose that we estimate an unrestricted, n-th order vector autoregressive representation (VAR) for x_t, with the lag depth n chosen on statistical grounds, which yields a vector of innovations ν_t:

$$(4.3) \qquad [I - \sum_{j=1}^{n} L^j \Theta(j)] x_t = \nu_t$$

where $\Theta(j)$ is the matrix of estimated coefficients at lag j. Since x_t is stationary, this can be inverted to obtain the estimated moving average representation:

$$(4.4) \qquad x_t = [I - \sum_{j=1}^{n} L^j \Theta(j)]^{-1} \nu_t$$

$$= \sum_{j=0}^{\infty} L^j C(j) \nu_t$$

where C(0)=I. Equating (4.1) and (4.4), we can see that the VAR innovations will be linear combinations of the underlying temporary and permanent shocks:

$$(4.5) \qquad \nu_t = A(0) e_t$$

where A(0) is a 2×2 matrix. To recover the underlying temporary and permanent shocks from the VAR innovations Blanchard and Quah (1989) thus suggest four restrictions. Three restrictions can be obtained by normalizing the variance of $e_{T,t}$ and $e_{P,t}$ to unity and requiring them to be orthogonal. Let Ω be the variance-covariance matrix of ν_t, then, using (4.5), these restrictions can be written:

$$(4.6) \qquad A(0) A(0)' = \Omega$$

From (4.1), (4.4) and (4.5) we can deduce the impulse response functions in terms of C(j) and A(0):

$$(4.7) \qquad A(j) = C(j)A(0)$$

Using (4.2) and (4.7) we can then deduce a fourth restriction on A(0):

$$(4.8) \qquad \kappa' \sum_{j=0}^{\infty} C(j)A(0)\kappa = 0$$

where $\kappa = (1\ 0)'$.

Taylor (1996) shows that there is not one unique decomposition that satisfies the Blanchard-Quah restrictions - in fact there are four distinct decompositions. To identify the Blanchard-Quah decomposition, Taylor (1996) demonstrates that some reasonably well specified underlying theoretical framework may generate (informally) the additional qualitative restrictions to achieve such identification. For example, one could use the standard underlying aggregate supply-aggregate demand framework with a long-run vertical supply curve to qualify the impulses of the temporary and permanent innovations to a system of real output and prices.

There is a direct relationship between the Blanchard-Quah decomposition and deriving the pure random walk component in x_t. In the Blanchard-Quah (1989) decomposition, the permanent component contains a random-walk and mean-reverting component. To identify the pure random-walk component we rewrite equation (4.1) as a common trends representation:

$$(4.9) \qquad \begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix} = \begin{bmatrix} a_{11}(1) & a_{12}(1) \\ a_{21}(1) & a_{22}(1) \end{bmatrix} \begin{bmatrix} \tau_{T,t} \\ \tau_{P,t} \end{bmatrix} + \begin{bmatrix} e^*_{T,t} \\ e^*_{P,t} \end{bmatrix}$$

where

$$\begin{bmatrix} e^*_{T,t} \\ e^*_{P,t} \end{bmatrix} = (1-L)^{-1} \begin{bmatrix} a_{11}(L)-a_{11}(1) & a_{12}(L)-a_{12}(1) \\ a_{21}(L)-a_{21}(1) & a_{22}(L)-a_{22}(1) \end{bmatrix} \begin{bmatrix} e_{T,t} \\ e_{P,t} \end{bmatrix}$$

$$\tau_{P,t} = \tau_{P,t-1} + e_{P,t}$$

$$\tau_{T,t} = \tau_{T,t-1} + e_{T,t}$$

and

$$a_{ik}(L) = \sum_{j=0}^{\infty} a_{ik}(j)L^j \qquad \text{for } i,k = 1,2 \ .$$

Clearly, $[e^*_{T,t} - e^*_{P,t}]' \sim I(0)$ while $\tau_{T,t}$ and $\tau_{P,t}$ are pure random walks, so that both $x_{1,t}$ and $x_{2,t}$ are shown to be the sum of two common stochastic trends and a stationary component. To recover the mean-reverting and random walk-components from the VAR we impose the restrictions consistent with Blanchard and Quah (1989) - equations (4.2), (4.6) and (4.8) - that $e_{T,t}$ has no long-run effect on $x_{1,t}$, $a_{11}(1)=0$, is thus equivalent to imposing the restriction that the stochastic trend ($\tau_{T,t}$) in equation (4.9) is suppressed. Thus, the random-walk and mean-reverting components can be obtained from the following time series representation for x_t:

$$(4.10) \qquad \begin{bmatrix} x_{1,t} \\ x_{2,t} \end{bmatrix} = \begin{bmatrix} 0 & a_{12}(1) \\ a_{21}(1) & a_{22}(1) \end{bmatrix} \begin{bmatrix} \tau_{T,t} \\ \tau_{P,t} \end{bmatrix} + \begin{bmatrix} e^*_{T,t} \\ e^*_{P,t} \end{bmatrix}$$

4.2 Robust Estimation: RALS and LAD

Least squares (LS) estimation is inefficient when the disturbances are non-Gaussian, a characteristic of most financial data series (Von Furstenberg and Jeon, 1989; Phillips, McFarland and McMahon, 1996). The difficulties that surround LS estimation with financial and economic data has resulted in a number of alternative robust estimation procedures, for example L-estimators, M-estimators, R-estimators (see Judge, Hill, Griffiths, Lütkepohl and Lee, 1988, ch. 22, for an accessible survey of robust estimation) and - more recently - the residuals augmented least square (RALS) approach (Im, 1996). Because the least squares procedure minimizes squared deviations, it places a relatively heavy weight on outliers, and in the presence of errors that are not normally distributed (for example, a more leptokurtic distribution) can lead to estimates that are extremely fragile. Thus the robust estimation procedure can be substantially more efficient in cases where - as in financial markets - innovations are known to have fat-tailed and, perhaps, skewed distributions (Badrinath and Chatterjee, 1988; Von Furstenberg and Jeon, 1989; Jansen and deVries, 1991; Phillips *et al.*, 1996). The feature of the leptokurtic distribution of financial asset returns is a theme in recent studies that use autoregressive conditional heteroscedasticity (ARCH) approaches to model conditional returns data (for example, Engle, 1982; Bollerslev, 1986; Bollerslev, Chou and Kroner, 1992) and empirical work on the unconditional distributions of returns (for example, Koedijk, Schafgans and deVries, 1990; Koedijk and Kool, 1992; Loretan and Phillips, 1994)

We investigate in Chapter 7 the sensitivity of the vector autoregressive representation decomposition as estimated by LS to alternative robust estimation procedures - the least absolute deviation (LAD) and the RALS (Im, 1996) estimators.

The LAD estimator (also known as the L_1-estimator) belongs to the class of L-estimators and is sometimes used as an alternative to LS particularly when the disturbances may be distributed as Cauchy or Student's t (i.e. fat-tailed). Calculation of the L-estimator is based on the method of regression quantiles described in Koenker and Bassett (1978) and Koenker and D'Orey (1987). The LAD estimation method has good propoerties in time series regression models (Bloomfield and Steiger, 1983), including models with an autoregressive unit root (Phillips, 1991). Moreover, if the disturbances follow a double expotential then the LAD estimator is equivalent to the maximum likelihood estimator (Judge *et al.*, 1988, ch.22). Butler, McDonald, Nelson and White (1990) also show that unlike LS estimators the LAD estimators are barely affected by an extreme outlier.

Consider the following simple regression,

$$(4.11) \qquad y_t = \beta' z_t + u_t \ , \qquad\qquad t = 1,\ldots.T$$

where $z_t = (1 \ \ x_t')'$, x_t is a $(k-1)\times 1$ vector of time series observed at time t, β' is the k-parameter vector that includes the intercept, and the residuals u_t are i.i.d. with distribution function symmetric around zero. The regression quantile family of estimators is based on minimizing the criterion function:

$$(4.11) \quad \min_{\beta} \left[\sum_{\{t|y_t \geq \beta' z_t\}} \theta |y_t - \beta' z_t| + \sum_{\{t|y_t < \beta' z_t\}} (1-\theta) |y_t - \beta' z_t| \right]$$

where the θth sample regression quantiles ($0<\theta<1$), and any linear function of them, are the possible L-estimators. Since the solution is the weighted sum of the absolute values of the residuals, outliers are given less importance than with ordinary least squares estimation. The LAD estimator is one example of a linear function of regression quantiles where all the weight is placed on $\theta=0.5$.[28] Thus, for the LAD estimator, the minimization problem is equivalent to finding that β which minimizes $\Sigma|y_t - \beta' z_t|$. We generate the LAD estimator β_L using the Barrodale-Roberts (1980) modified simplex algorithm.

The asymptotic distribution of the LAD estimator β_L is given by

$$(4.13) \qquad \sqrt{T}[\beta_L - \beta] \rightarrow N(0,[2f(0)]^{-2} Q^{-1})$$

where Q is a positive definite matrix equal to $\text{plim}_{T\rightarrow\infty} T^{-1}X'X$, and X is the matrix of regressors. The term $[2f(0)]^{-2}$ is the asymptotic variance of the sample median from samples with distribution function F and density function f, with its value at the median given by $f(0)$.

[28] Varying θ between 0 and 1 yields a set of regression quantile estimators, $\beta(\theta)$. Therefore, alternative linear combinations of weighted regression quantiles have been proposed, for example, the trimean scheme suggested by Tukey (1977), the Gastwirth (1966) scheme, and the five- quantile estimator (Judge *et al.*, 1988, ch 22).

Cox and Hinkley (1974, p. 470) recommend that $f(0)$ be estimated by $f(0)=2d/T(\hat{u}_{(m+d)} - \hat{u}_{(m-d)})$ where m and d are integers, $(\hat{u}_{(1)}, \hat{u}_{(2)}, \hat{u}_{(3)}, ...\hat{u}_{(T)})$ are the ordered LAD residuals, and $\hat{u}_{(m)} = 0$ (with $m \approx T/2$) is a central LAD residual. The parameter d tells us what differential to use when selecting ordered residuals to use in computing the covariance matrix, equation (4.13) and the method of Bofinger (1975) and Siddiqui (1960) can be used to estimate d: $d=T^{(-1/5)}[(4.5\varphi^4(\Phi^{-1}(0.5)))/(2\Phi^{-1}(0.5)^2+1)^2]^{(1/5)}$, where φ and Φ represent the normal density and cumulative normal density, respectively.

The RALS procedure identified by Im (1996) is very recent and thus requires a more comprehensive discussion. Consider the following simple regression

$$(4.14) \qquad y_t = \phi' z_t + u_t$$

where $z_t = (1 \;\; x_t')'$, x_t is a $(k-1)\times 1$ vector of time series observed at time t, $\phi = (\alpha \;\; \beta')'$ is the parameter vector where α is the intercept and β is the $(k-1)\times 1$ vector of parameters of interest.

The standard LS estimator applied to (4.14) can be interpreted as a method of moments estimator based on the normal equations:

$$(4.15) \qquad E[z_t u_t] = 0$$

When the distribution of u_t is skewed and leptokurtic, however, there will be two further moment conditions which can be exploited to yield a more efficient estimator, viz:

$$(4.16) \qquad E[z_t(u_t^3 - \mu_3)] = 0$$

and

$$(4.17) \qquad E[z_t(u_t^2 - \sigma^2)] = 0$$

where σ^2 is the variance and μ_3 is the third central moment of u_t . The RALS estimator can be interpreted as a generalized method of moments (GMM) estimator based on the moment conditions (4.15), (4.16) and (4.17). Im (1996) shows that this GMM estimator of β, β^* say, can in fact be simply computed from ordinary least squares applied to (4.14) augmented by $\hat{w}_t = [(\hat{u}_t^3 - 3\hat{\sigma}^2\hat{u}_t)\ (\hat{u}_t^2 - \hat{\sigma}^2)]'$:

$$(4.18) \qquad y_t = \alpha + \beta' z_t + \gamma' \hat{w}_t + e_t$$

where $\hat{u}_t$ denotes the LS residual and $\hat{\sigma}^2$ the standard residual variance estimate obtained from LS applied to (4.14). The RALS estimator is thus given by

$$(4.19) \qquad \beta^* = (\tilde{X}' M_{\tilde{W}} \tilde{X})^{-1} \tilde{X}' M_{\tilde{W}} Y$$

where the idempotent matrix $M_{\tilde{W}}$ is

$$(4.20) \qquad M_{\tilde{W}} = I_T - \tilde{W}'(\tilde{W}'\tilde{W})^{-1}\tilde{W}$$

where I_T is the T×T identity matrix and $\tilde{N} = (\tilde{n}_1\ \tilde{n}_2 \ldots \tilde{n}_T)'$, $\tilde{n}_t = n_t - T^{-1}\Sigma_1^T n_t$ for (N,n)=(X,x),(Y,y),(W,w) and t=1,....T.

The asymptotic distribution of the RALS estimator is given by

$$(4.21) \qquad \sqrt{T}(\beta^* - \beta) \rightarrow N(0\,,\sigma_A^2 Var(X_t)^{-1})$$

where

$$\sigma_A^2 = \sigma^2 - \frac{\mu_3^2(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2) - 2\mu_3(\mu_4 - 3\sigma^4)(\mu_5 - 4\mu_3\sigma^2) + (\mu_4 - 3\sigma^4)^2(\mu_4 - \sigma^4)}{(\mu_4 - \sigma^4)(\mu_6 - 6\mu_4\sigma^2 + 9\sigma^6 - \mu_3^2) - (\mu_5 - 4\mu_3\sigma^2)^2}$$

and μ_i denotes the i-th central moment of u_t.

In practice, σ_A^2 can be consistently estimated by replacing each of the μ_i with the corresponding sample moments, using the LS residuals, yielding $\hat{\sigma}_A^2$, and the covariance matrix for β^* can be consistently estimated by

$$(4.22) \qquad \widehat{\mathrm{Var}}(\beta^*) = \hat{\sigma}_A^2(\tilde{X}'M_{\tilde{W}}\tilde{X})^{-1}$$

Note that, for normally distributed errors, the RALS estimator is asymptotically identical to the LS estimator and there is no efficiency gain since $\sigma_A^2 = \sigma^2$. In general, however, the asymptotic efficiency gain from employing RALS as opposed to LS can be gauged from the statistic $\eta^2 = \sigma_A^2/\sigma^2$ (which is small for large efficiency gains) and Im (1996) shows that this gain can be substantial for a range of alternative non-normal error distributions. In practice, the efficiency gain in any particular application can be gauged from $\hat{\eta} = \hat{\sigma}_A^2/\hat{\sigma}^2$.

Im (1966) suggests that the decision as to whether to employ the RALS estimator might be based on the results of tests of normality of the error distribution such as the Jarque and Bera (1987) test, which is in fact based on the estimated coefficients of skewness and excess kurtosis.

Extending the results of Hansen (1995), Im (1966) also suggests a unit root test based on RALS estimator which is a straightforward extension of the standard Dickey-Fuller test. This simply involves estimating the auxiliary Dickey-Fuller regression and the covariance matrix of the estimated parameters by RALS and constructing the test statistic in the normal way. For example, to test for a unit root in the stochastic process generating ζ_t, set $y_t = \Delta\zeta_t$ and $x_t = \zeta_{t-1}$ and construct the RALS Dickey-Fuller statistic (RALSDF) as $\tau_A = \beta^* / V(\beta^*)^{1/2}$.

Applying the results of Hansen (1995), Im (1996) shows that the limiting distribution of τ_A is a convex mixture of the Dickey-Fuller and normal distributions:

$$(4.23) \qquad \tau_A \rightarrow \eta \frac{\int_o^1 \tilde{B}_1 dB_1}{\int_o^1 (\tilde{B}_1^2)^{1/2}} + (1-\eta^2)^{1/2} N(0,1)$$

where B_1 and B_2 are standard independent Brownian motions, $\tilde{B}_1$ is the demeaned B_1 and η^2 is the efficiency gain statistic as before, $\eta^2 = \sigma_A^2/\sigma^2$.

Im (1996) conducts a number of Monte Carlo experiments with τ_A and demonstrates that this statistic is dramatically more powerful than the standard Dickey-Fuller statistic when the error sequences are driven by non-normal errors and that, for a sample size of a hundred or more, there is little size distortion.

Chapter 5

ESTIMATING THE TEMPORARY AND PERMANENT COMPONENTS IN U.S. STOCK PRICE MOVEMENTS: AGGREGATE DEMAND AND SUPPLY INNOVATIONS

5.1 Introduction

Studies that have tested the mean reversion hypothesis have tended to concentrate on the US, principally because the size of the market and the unavailability of high quality non-overlapping long time series of stock prices data for other countries that traditional techniques requires. For comparison purposes we take the US market as the starting point in the empirical evaluation of the temporary and permanent components of stock prices.

This chapter uses a restricted two-variable vector autoregressive system, a variant of the Blanchard and Quah (1989) technique, to decomposes real US stock prices into two components - a component that does not have a long-run effect on stock prices (temporary component) and a component that has a long-run effect on stock prices (permanent component). Taking the two variables as real stock prices and consumer prices, the macro model outlined in Chapter 3 allows us to relate the temporary and permanent components of stock price movements to aggregate macroeconomic demand and supply disturbances. In particular, in the context of the macro model, aggregate demand shocks have only temporary effects on real stock prices, that is, stock prices are mean-reverting, while supply shocks may affect the level of real stock prices permanently.[29] Thus we interpret the temporary component as the response of stock prices due to aggregate demand innovations and the permanent component as the response of stock prices due to aggregate supply innovations. In this context, the interrelationship between macroeconomic and financial variables allows us to estimate a temporary component in real stock prices that is mean reverting. We investigate the size and significance of this temporary (or mean-reverting) component in US stock prices by placing the appropriate structural restrictions on a VAR system, corresponding to a long-run vertical supply curve framework in which, in line with the illustrative macro model, only supply shocks have a long-run effect on real stock prices. Our model differs from the univariate models of Fama and French (1988a) and Poterba and Summers (1988), in that our model does not restrict the permanent and temporary components to being a pure random walk process and an AR(1) process, respectively. We do not specify the form of the permanent and temporary components, and the two components can be identified by the simple macro model.

[29]Aggregate demand shocks have a only a short-run effect on real stock prices, but a long-run effect on consumer prices. Whereas, aggregate supply shocks has a long-run effect on both real stock prices and consumer prices.

5.2 Data and Preliminary Tests

Monthly data for the United States were obtained from the Center for Research in Securities Prices (CRSP). The sample period is 1925:12 to 1995:12. The data series of interest are the real stock price index and the consumer price index. The real stock price index is constructed by deflating the stock price index by the consumer price index. The stock price index is the S&P500 index obtained from the CRSP stock files indices and the consumer price index obtained from the SBBI files. The logarithm of the real stock price index and the consumer price index is denoted by q_t and p_t, respectively. The logarithm of the real stock price and consumer price series are presented in Figures 5.1 and 5.2 (the first difference of each series are presented in panel b of the figures). The figures identify a number of key periods in United States history. There is evidence that the behaviour of stock return and inflation was unusual in the 1929-39 decade, the period around the Great Depression. Therefore, empirical tests that include these data for the 1929-39 period are suspect and findings may be heavily influenced by that period's data (see, for example, Fama and French, 1988a; Poterba and Summers, 1988; Schwert, 1990a,b; Kim *et al.*, 1991). Other noticeable periods are the 1945-48 period for inflation and the October 1987 stock market crash, for stock returns.

Table 5.1 and Table 5.2 reports some summary statistics on the variable series of interest. The first sub-period reveals a relatively low mean and high variance of the stock return and inflation series - consistent with the discussion above. The sample autocorrelations reveal some degree of persistence in both series as they tend to die off slowly, for the full period and the individual sub-periods. The first-order autocorrelations values close to one suggest that the series are non-stationary. This impression is borne out by Table 5.3 which reports the unit root and cointegration tests for each series. The sequential procedure employed in testing for unit roots follows Dickey and Pantula (1987) in order to ensure that only one unit root is present in the series. The unit root tests are the augmented Dickey-Fuller (ADF) and the Phillips-Perron Z_t (PP) tests, for the null hypothesis that the series in question is I(1) (see Dickey and Fuller, 1979,1981; Perron, 1988). A lag length of six was chosen. Both tests cannot reject the hypothesis that the series are first-difference stationary, ie. I(1). [30, 31]

As a test for cointegration, the results of the ADF test for a unit root in the least squares residual from a regression of p_t onto q_t and a constant are reported in Table 5.3 (final row). As in the case of unit root tests, a lag length of six was chosen. The null hypothesis of no cointegration cannot be rejected at the 5 percent level of significance.[32, 33] Cointegration implies a common trends approach (Stock and Watson, 1988; Cochrane, 1994) - this issue was discussed

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[30]Different lag depths used to calculate the ADF and PP test statistics (not reported) could not reject, at standard significance levels, the hypothesis that the consumer price and real stock price series are each realizations of I(1) processes.

[31]Throughout this thesis, unless otherwise specified, we use a nominal significance level of 5 percent in hypothesis testing.

[32]The null hypothesis of no cointegration could not be rejected for different lag lengths.

[33]The unit root and cointegration findings are consistent with other studies (see, for example, Lee, 1995).

in Chapter 4, section 4.1.

Table 5.1: Summary Statistics, Full Period

	q_t	Δq_t	p_t	Δp_t
Mean	-	0.21	-	0.26
σ	-	5.72	-	0.56
$\rho(k)$				
k= 1	0.99*	0.08	1.00*	0.56*
2	0.98*	-0.02	0.99*	0.40*
3	0.97*	-0.12	0.99*	0.38*
4	0.96*	0.03	0.99*	0.38*
5	0.96*	0.09	0.99*	0.31*
6	0.95*	-0.02	0.98*	0.29*
7	0.94*	0.02	0.98*	0.34*
8	0.93*	-0.04	0.98*	0.34*
9	0.92*	0.06	0.97*	0.30*
10	0.91*	0.00	0.97*	0.29*
11	0.90*	-0.02	0.97*	0.31*
12	0.89*	0.01	0.97*	0.32*

Notes: The sample period is 1925:1-1995:12. The mean and standard deviation, σ, are expressed in percentage terms. $\rho(k)$ = autocorrelation between x_t and x_{t-k}. p_t is the natural logarithm of the consumer price index; q_t is the natural logarithm of real stock prices. Δ=(1-L) denotes the first difference. An asterisk denotes the sample autocorrelation is at least two standard deviations to the left or to the right of its expected value under the hypothesis that the true autocorrelation is zero.

Table 5.2: Summary Statistics, Sub-Periods

	1925:12 - 1948:12				1949:1 - 1995:12			
	q_t	Δq_t	p_t	Δp_t	q_t	Δq_t	p_t	Δp_t
Mean	-	-0.03	-	0.11	-	0.33	-	0.33
σ	-	8.11	-	0.83	-	4.08	-	0.35
$\rho(k)$								
k= 1	0.96*	0.10	0.99*	0.51*	0.99*	0.05	1.00*	0.62*
2	0.91*	-0.02	0.97*	0.31*	0.97*	-0.03	0.99*	0.54*
3	0.86*	-0.19*	0.96*	0.31*	0.95*	0.03	0.99*	0.48*
4	0.83*	0.02	0.94*	0.33*	0.94*	0.04	0.98*	0.44*
5	0.80*	0.08	0.92*	0.23*	0.92*	0.11	0.98*	0.45*
6	0.76*	-0.01	0.90*	0.21*	0.91*	-0.05	0.98*	0.41*
7	0.72*	0.04	0.88*	0.27*	0.89*	-0.02	0.97*	0.42*
8	0.68*	0.08	0.86*	0.26*	0.87*	-0.03	0.97*	0.45*
9	0.63*	0.09	0.85*	0.21*	0.86*	0.00	0.96*	0.45*
10	0.57*	-0.01	0.83*	0.20*	0.85*	-0.00	0.96*	0.44*
11	0.52*	-0.03	0.81*	0.24*	0.83*	0.01	0.95*	0.41*
12	0.47*	-0.01	0.79*	0.26*	0.82*	0.03	0.95*	0.39*

Notes: The sample periods are 1925:12-1948:12 and 1949:1-1995:12. The mean and standard deviation, σ, are expressed in percentage terms. $\rho(k)$ = autocorrelation between x_t and x_{t-k}. p_t is the natural logarithm of the consumer price index; q_t is the natural logarithm of real stock prices. Δ=(1-L) denotes the first difference. An asterisk denotes the sample autocorrelation is at least two standard deviations to the left or to the right of its expected value under the hypothesis that the true autocorrelation is zero.

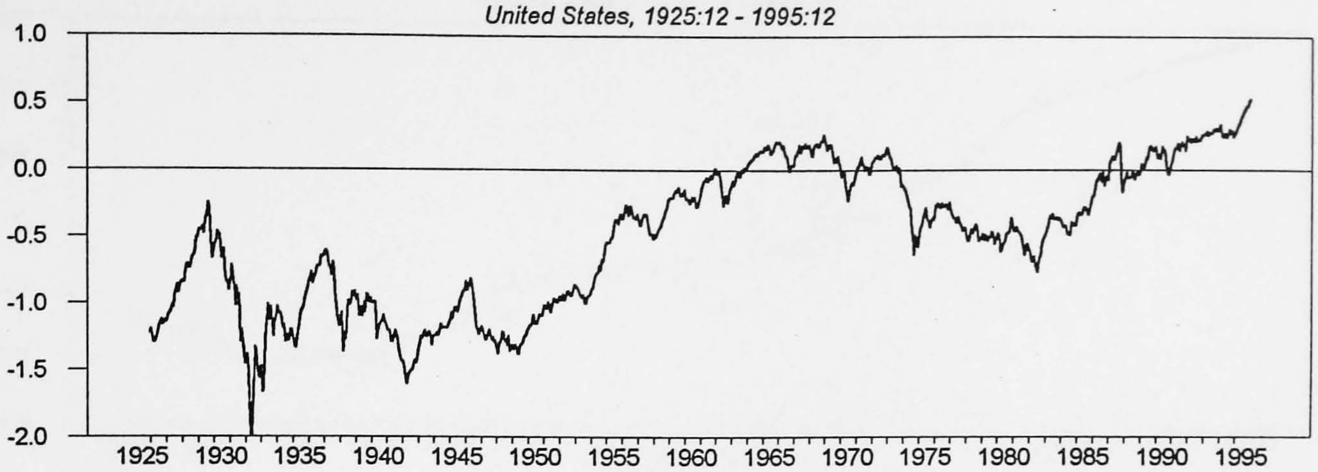
Table 5.3: Unit Root and Cointegration Tests: Consumer Prices and Real Stock Prices

	Full Period 1925:12-1995:12		First Sub-Period 1925:12-1948:12		Second Sub-Period 1949:1-1995:12	
	ADF	PP	ADF	PP	ADF	PP
q_t	-1.29	-1.28	-2.27	-2.39	-2.15	-2.02
Δq_t	-10.44	-26.51	-5.95	-14.84	-8.40	-22.60
$\Delta^2 q_t$	-20.04	-74.77	-12.14	-42.18	-14.05	-61.83
p_t	1.79	3.57	0.06	1.31	0.65	2.50
Δp_t	-5.81	-16.14	-3.57	-9.78	-4.12	-12.37
$\Delta^2 p_t$	-17.75	-55.23	-9.74	-30.60	-14.88	-48.89
μ_t	-1.55	-	0.06	-	-0.46	-

Notes: p_t is the natural logarithm of the consumer price index; q_t is the natural logarithm of real stock prices. μ_t is the ordinary least squares regression of p_t onto q_t and a constant. The unit root tests are the Augmented Dickey-Fuller test statistic (ADF) and the Phillips-Perron Z_t test statistic (PP), without time trend and with constant, for the null hypothesis that the series is unit root (see, Dickey and Fuller, 1979, 1981; Perron, 1988); the lag truncation was set at six. For a 5% significance level the critical PP and ADF is -2.88. The cointegration test is the augmented Dickey-Fuller test; for a 5% significance level the critical value is -3.17 (see, Fuller, 1976, pp. 371-3; and Engle and Granger, 1987).

Figure 5.1: Real Stock Price Index, S&P500 (in logs)

United States, 1925:12 - 1995:12



Real Stock Returns, %

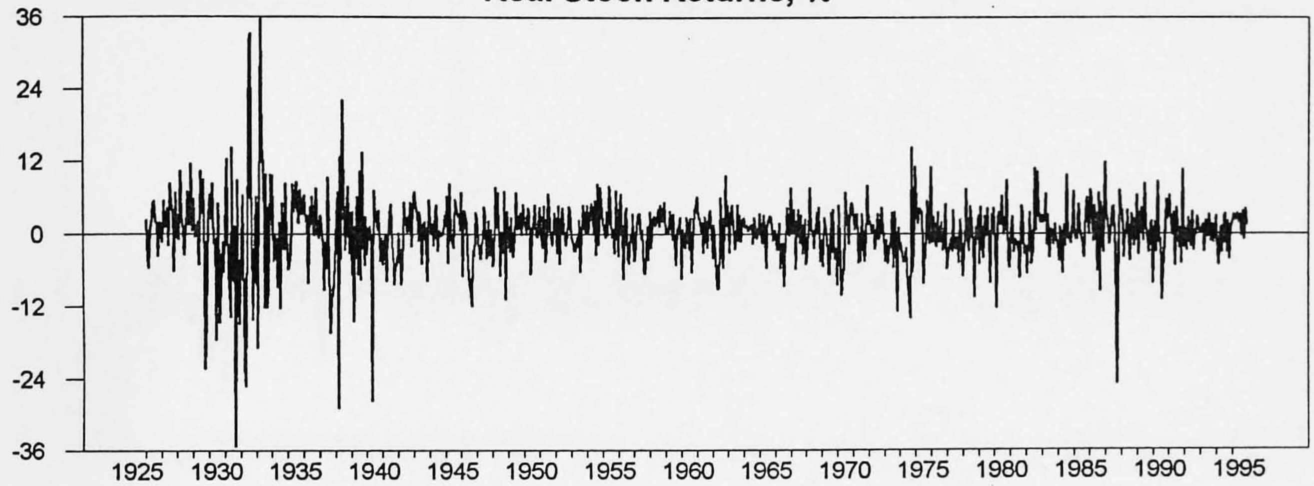
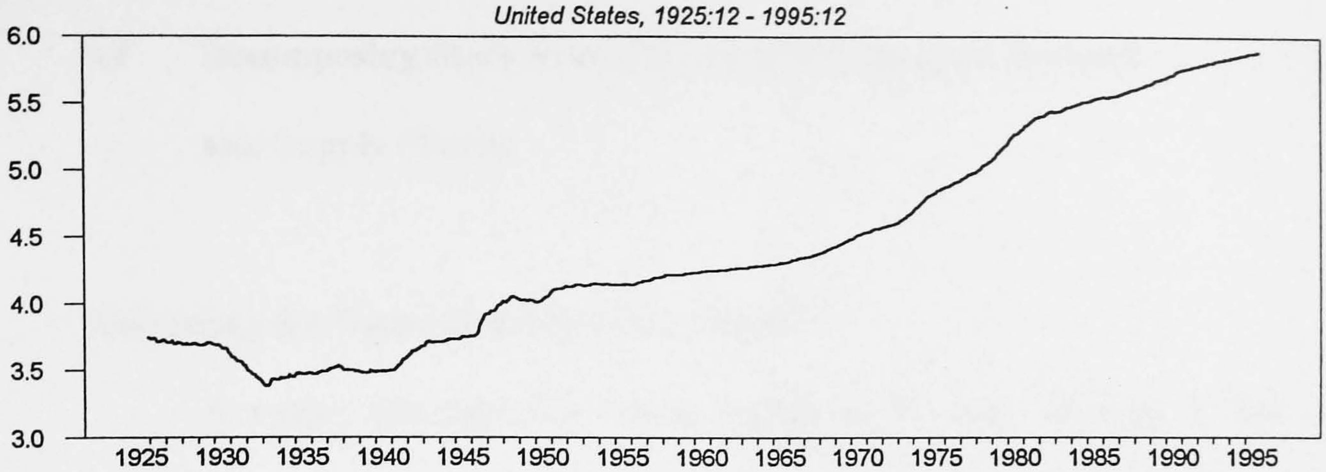
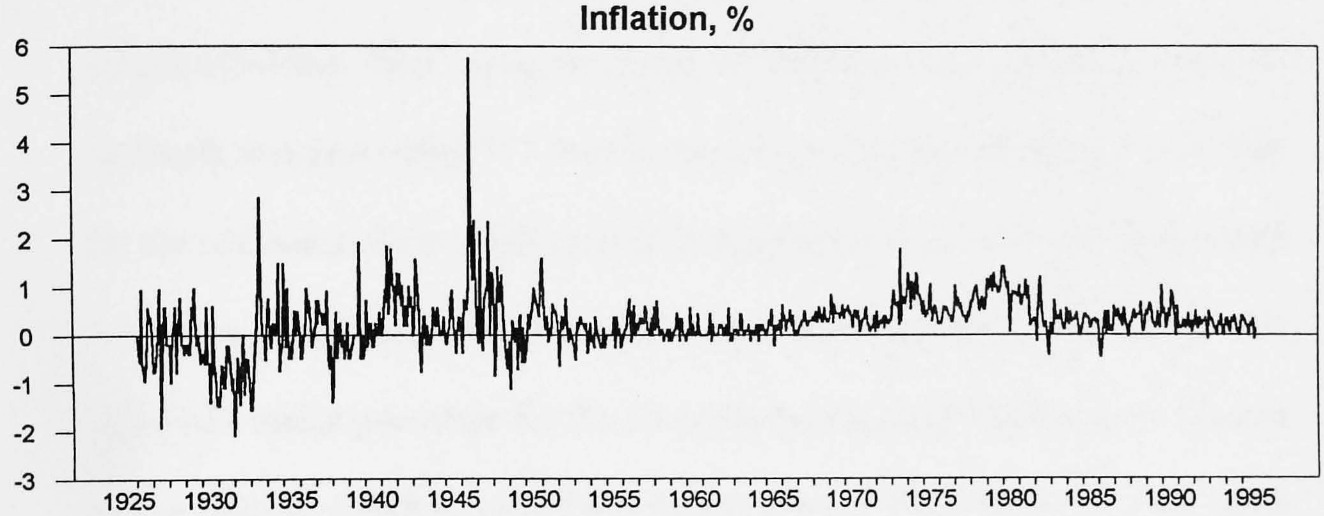


Figure 5.2: Consumer Price Index (in logs)

United States, 1925:12 - 1995:12



Inflation, %



5.3 Decomposing Stock Price Movements: Aggregate Demand and Supply Shocks

Estimating the Vector Autoregressive Process

A vector autoregressive representation of $[(1-L)q_t \quad (1-L)p_t \ ]'$ was estimated prior to effecting the decomposition.[34] The lag length for the VAR was chosen as follows. First, using the Bayes Information Criterion (BIC), the initial lag length was determined.[35,36] Second, using the Ljung-Box Q-statistic we tested for the whiteness of the residuals and the lag depth increased (if necessary) until they were approximately white noise. The chosen lag depth was seven. We followed a similar procedure for the sub-periods, a lag depth of three was chosen for the 1925:12-1948:12 period and for the 1949:1-1995:12 period a lag depth of nine was chosen.

Permanent and Temporary Components

Given the estimates of the VAR parameters (presented in Table 5.4) and the covariance matrix of VAR residuals (presented in Table 5.5), we then carried out the decomposition as described in Chapter 4, section 4.1. The estimated A(0)

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[34]Seasonal dummies were included in the VAR.

[35]In a Monte Carlo analysis of alternative criteria to determine lag length of VARs, Lütkepohl (1985) favours the Schwarz-multivariate BIC. Lütkepohl finds that the BIC criterion chooses the correct lag order most often, and the resulting VAR models provide the best forecasts.

[36]For the full sample period, 1925:12-1995:12, the BIC chose a lag length of four, the Akaike Information Criterion (AIC) chose nine; for the first sub-period, 1925:12-1948:12, BIC chose one and the AIC five; and for the second sub-period, 1949:1-1995:12, the BIC chose two and the AIC chose nine.

matrix, presented in Table 5.6, is used to construct the structural impulse responses described by equation (4.7).

The underlying model outlined in Chapter 3, section 3.1, used to impose qualitative restrictions on the VAR decomposition generates the cumulative impulse response functions presented in Figure 5.3 - 5.5. These illustrate the effect of a one unit (standard deviation) shock to the level of real stock prices and the level of consumer prices.

There are a number of interesting features that are worth noting. Real stock prices increase as a result of both positive aggregate demand (temporary) and aggregate supply (permanent) shocks. By construction, an aggregate demand shock results in only a temporary rise in real stock prices. However, as is evident in Figure 5.3, the temporary shock to real stock prices is quite persistent and relatively large for around the first twelve months; slowly reverting to their original value. The temporary shock has a half-life of 13 months. This finding is consistent with a slowly decaying stationary component, similar to other studies, for example, Fama and French (1988a).

A permanent shock causes real stock prices to rise, continuously for around the first six months, followed by a large fall (or reversal), then rising sharply for the next 12 months and thereafter slowly increasing towards steady state. The behaviour of the impulse response function indicates that the permanent component is unlikely to be a pure random walk but also contains a mean-reverting element. As predicted by the macro model, a permanent (aggregate supply) shock to consumer prices is negative, whereas a temporary (aggregate demand) shock is positive, with both disturbances having a long-run effect on consumer prices.

The sub-periods reveal some contrasting findings. For the first sub-period, 1925:12-1948:12, an aggregate demand shock to stock prices is positive, with a half-life of 4 months. The temporary shock to stock prices is smaller and less persistent than for the full sample period. In contrast, the aggregate supply shock to real stock prices is larger and less persistent than the full sample period. More importantly, the response of a permanent shock to stock prices is for prices to rise and then decline to their stable path. This reversal feature in the response of stock prices to a permanent shock could indicate a substantial mean-reverting component in the permanent component of stock prices.

The second sub-period, 1949:1-1995:12, is not subject to the unusual stock price and consumer price behaviour as evident of the 1925:12-1948:12 period. A temporary shock to stock prices increases stock prices with a half-life of 18 months. A permanent shock to stock prices increases stock prices, with only a very small reversal at the 12th month.

The response of consumer prices is as predicted by the macro model for the second sub-period. Consumer prices fall in response to an aggregate supply (permanent) disturbance and rise in response to an aggregate demand (temporary) disturbances. However, for the first sub-period consumer prices increase (in the long run) in response to an aggregate supply (permanent) disturbances. Although this is not inconsistent with the macro model (aggregate demand-aggregate supply), it occurs during a period of unusual behaviour - the Great Depression and World War II periods - and reflects various complex interactions and dynamic effects which are not captured for this period in the normal comparative static approach. In the context of the period in question there are a number of potential reasons for these findings; for example, it could be difficult for the model to distinguish between aggregate demand and aggregate supply disturbances, in that aggregate supply disturbances could be interpreted as aggregate demand disturbances. As noted by Blanchard and Quah (1989, p. 659) there is nothing in the identifying restrictions which "eliminate for example the possibility that supply disturbances directly affect aggregate demand". Therefore, "the assumption that the two disturbances are uncorrelated does not restrict the channels through which demand and supply disturbances affect" stock prices and consumer prices (in our case). More importantly for this study, as discussed above, including this time period in the analysis is suspect and likely to influence the results. It is for this reason that we will primarily concentrate on the second sub-period, 1949:1-1995:12.

The decomposition generates three components of stock price movements - temporary (aggregate demand), permanent (aggregate supply) and deterministic (trend and seasonals). Therefore, by cumulating each shock over time and then in turn adding each series together we can show the contribution of each component to real stock prices. The resulting series are presented in Figures 5.6-5.8. The figures illustrates the three components of real stock prices - temporary, permanent and deterministic. The plot line labelled deterministic component is the trend and seasonal elements of real stock prices; the line labelled temporary component adds the cumulated temporary shocks to the deterministic component line. Finally, the line labelled permanent component (by construction corresponding to the natural logarithm of real stock prices) adds the cumulative permanent innovations to the temporary and deterministic components.[37] Thus, the difference between the deterministic component line and the temporary component line measures the temporary innovations in real stock prices. Similarly, the difference between the temporary component line and the permanent component line measures the permanent innovations in real stock prices.

The temporary component presented in Figures 5.6-5.8 indicates that the temporary innovations are stationary around the deterministic component, with substantial deviations in periods of large swings in real stock prices - this evidence is consistent with the notion of noise traders (see, De Long *et al.*, 1990; Shleifer and Summers, 1990). The size of the temporary innovations are small relative to the permanent innovations, however, as shown below, the temporary component explains a significant proportion of the total variation in real stock price movements.

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[37]Note, since the natural logarithm of real stock prices is the sum of the three cumulated shocks, normalising the deterministic component to equal the first (usable) stock price observation, the plot line labelled permanent component is identical to the natural logarithm of real stock prices.

Table 5.4: VAR Parameter Estimates

		1925:12-95:12	1925:12-48:12	1949:1-95:12
(1-L) q_t	(1-L) q_{t-1}	0.081790*	0.091146	0.025785
		(0.035205)	(0.061838)	(0.044021)
	(1-L) q_{t-2}	-0.000469	-0.007217	-0.046170
		(0.035314)	(0.062336)	(0.043976)
	(1-L) q_{t-3}	-0.112517*	-0.160925*	0.022116
		(0.035415)	(0.062956)	(0.044011)
	(1-L) q_{t-4}	0.049957		0.021070
		(0.035582)		(0.044064)
	(1-L) q_{t-5}	0.096034*		0.117857*
		(0.035390)		(0.043817)
	(1-L) q_{t-6}	-0.064974		-0.075472
		(0.035542)		(0.043601)
	(1-L) q_{t-7}	0.028339		-0.019568
		(0.035424)		(0.043665)
	(1-L) q_{t-8}			-0.067176
				(0.043616)
	(1-L) q_{t-9}			-0.006167
				(0.043793)
	(1-L) p_{t-1}	-0.678508	-0.317856	-1.489383*
		(0.453284)	(0.724889)	(0.733907)
	(1-L) p_{t-2}	-0.117947	-0.227700	0.372705
		(0.490590)	(0.792098)	(0.772816)
	(1-L) p_{t-3}	-0.780243	-0.231950	-1.877680*
		(0.490146)	(0.718700)	(0.780424)
	(1-L) p_{t-4}	0.624656		2.256308*
		(0.484831)		(0.776039)
	(1-L) p_{t-5}	0.252274		-0.121722
		(0.487382)		(0.775917)
	(1-L) p_{t-6}	-0.046656		-0.076319
		(0.484837)		(0.778005)
	(1-L) p_{t-7}	-0.135768		-0.561751
		(0.448811)		(0.776411)
	(1-L) p_{t-8}			0.354553
				(0.766627)
	(1-L) p_{t-9}			-1.965210
				(0.706557)

Statistics:			
Number of Usable obs.	833	273	554
R^2	0.07	0.09	0.10
Sum of Squared Errors	2.56	1.64	0.84
Ljung-Box Q(36)	46.69 [0.11]	36.65 [0.44]	23.38 [0.95]

$(1\text{-}L)p_t$	$(1\text{-}L)\,q_{t-1}$	0.004355	0.004094	-0.002098
		(0.002700)	(0.005206)	(0.002616)
	$(1\text{-}L)\,q_{t-2}$	0.009361*	0.015370*	-0.000388
		(0.002709)	(0.005248)	(0.002613)
	$(1\text{-}L)\,q_{t-3}$	0.001364	0.000798	-0.004463
		(0.002716)	(0.005300)	(0.002615)
	$(1\text{-}L)\,q_{t-4}$	0.001648		-0.000174
		(0.002729)		(0.002619)
	$(1\text{-}L)\,q_{t-5}$	-0.003254		-0.003521
		(0.002714)		(0.002604)
	$(1\text{-}L)\,q_{t-6}$	-0.001332		0.002080
		(0.002726)		(0.002591)
	$(1\text{-}L)\,q_{t-7}$	0.000186		0.002763
		(0.002717)		(0.002595)
	$(1\text{-}L)\,q_{t-8}$			0.006408*
				(0.002592)
	$(1\text{-}L)\,q_{t-9}$			-0.001839
				(0.002602)
	$(1\text{-}L)\,p_{t-1}$	0.408808*	0.454080*	0.373166*
		(0.034766)	(0.061026)	(0.043613)
	$(1\text{-}L)\,p_{t-2}$	0.029911	-0.015558	0.171666*
		(0.037627)	(0.066684)	(0.045925)
	$(1\text{-}L)\,p_{t-3}$	0.091670*	0.217475*	-0.006438
		(0.037593)	(0.060502)	(0.046377)
	$(1\text{-}L)\,p_{t-4}$	0.139255*		0.014831
		(0.037186)		(0.046117)
	$(1\text{-}L)\,p_{t-5}$	0.008546		0.071210
		(0.037381)		(0.046109)
	$(1\text{-}L)\,p_{t-6}$	-0.019904		0.019437
		(0.037186)		(0.046234)
	$(1\text{-}L)\,p_{t-7}$	0.148462*		0.086763
		(0.034428)		(0.046139)
	$(1\text{-}L)\,p_{t-8}$			0.057910
				(0.045557)
	$(1\text{-}L)\,p_{t-9}$			0.082521*
				(0.041988)
Statistics:				
Number of Usable obs.		833	273	554
R^2		0.42	0.38	0.53
Sum of Squared Errors		0.02	0.01	0.00
Ljung-Box Q(36)		51.18 [0.05]	48.54 [0.08]	48.09 [0.09]

Notes: The figures in parenthesis denote estimated standard errors. The deterministic parameters are not reported. An asterisk denotes significantly different from zero at the 5 percent level. Square brackets associated with the Ljung-Box Q-statistics for the residuals (for lags 1 through 36) denotes significance level. R^2 is the coefficient of determination.

Table 5.5: Covariance Matrix of VAR Residuals

1925:12-1995:12	$\begin{bmatrix} 3.0697e-3 & -9.7364e-6 \\ -9.7364e-6 & 1.8058e-5 \end{bmatrix}$
1925:12-1948:12	$\begin{bmatrix} 5.9985e-3 & -1.4062e-6 \\ -1.4062e-6 & 4.2514e-5 \end{bmatrix}$
1949:1-1995:12	$\begin{bmatrix} 1.5086e-3 & -1.1859e-5 \\ -1.1859e-5 & 5.3276e-6 \end{bmatrix}$

Table 5.6: A(0) Matrix

1925:12-1995:12	$\begin{bmatrix} 0.0181 & 0.0524 \\ 3.9566e-3 & -1.5503e-3 \end{bmatrix}$
1925:12-1948:12	$\begin{bmatrix} 0.0145 & 0.0761 \\ 6.4020e-3 & -1.2360e-3 \end{bmatrix}$
1949:1-1995:12	$\begin{bmatrix} 0.0252 & 0.0295 \\ 1.5420e-3 & -1.7175e-3 \end{bmatrix}$

Figure 5.3: Cumulative Impulse Response Functions

United States, 1925:12 - 1995:12

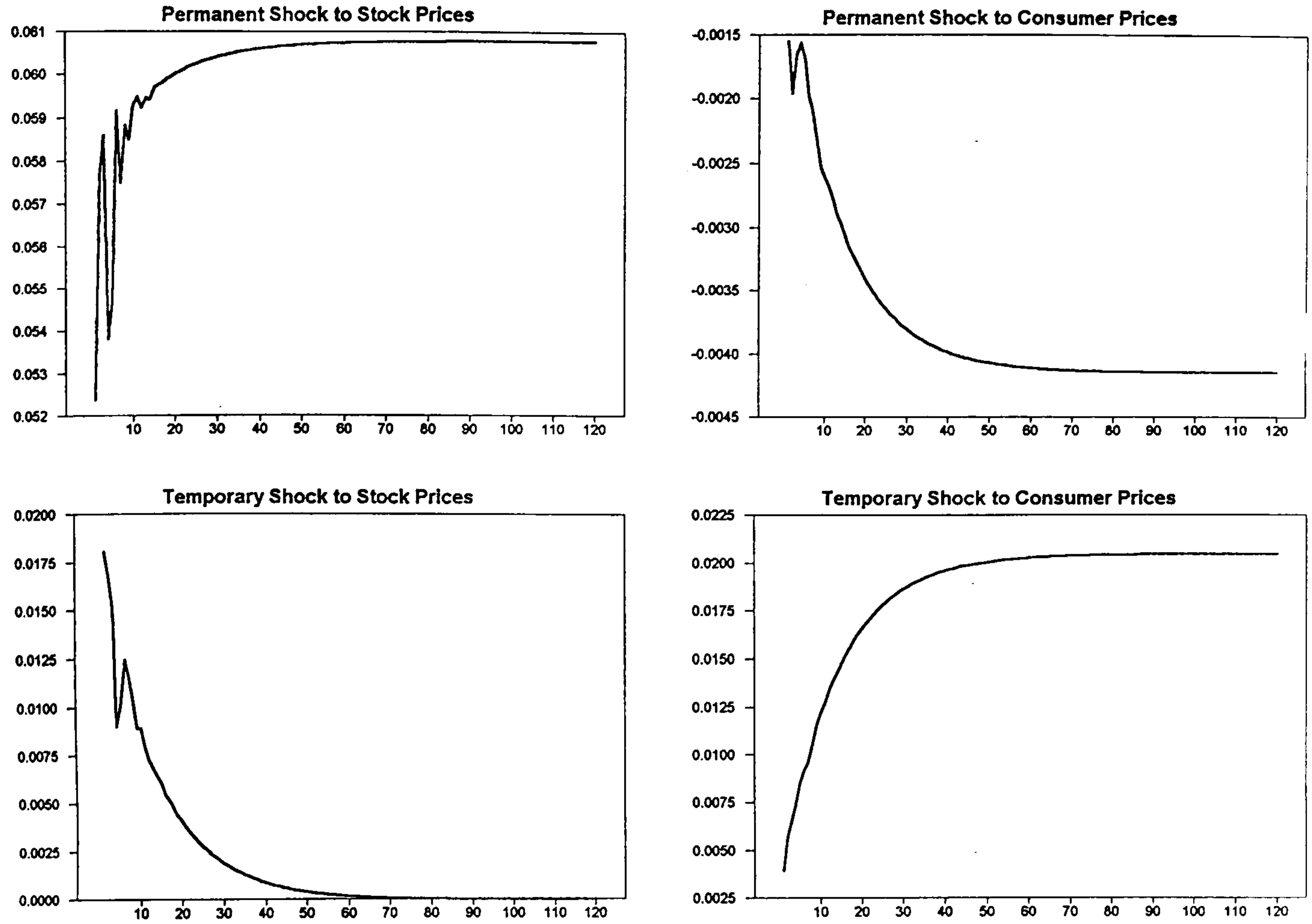


Figure 5.4: Cumulative Impulse Response Functions

United States, 1925:12 - 1948:12

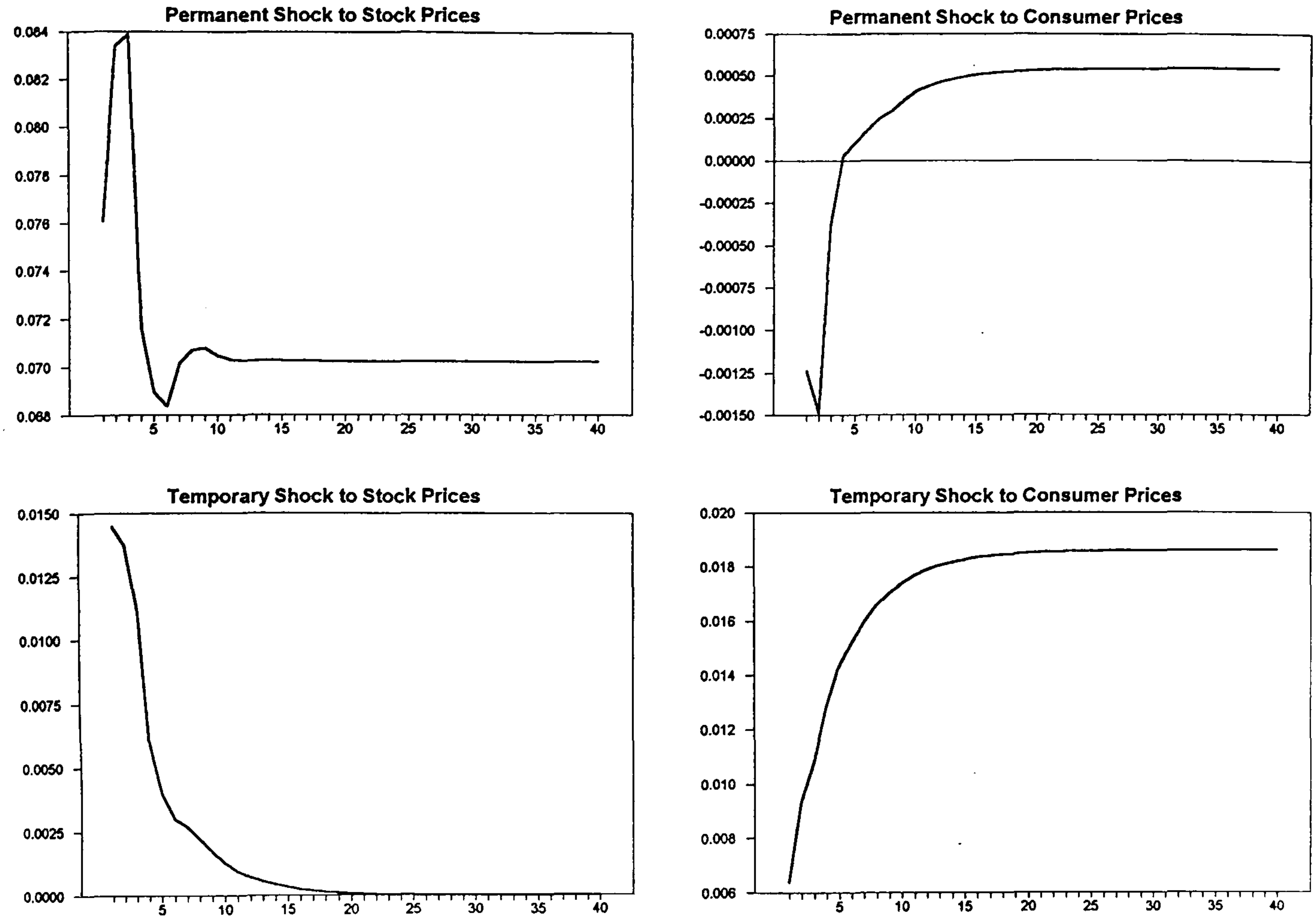


Figure 5.5: Cumulative Impulse Response Functions

United States, 1949:1 - 1995:12

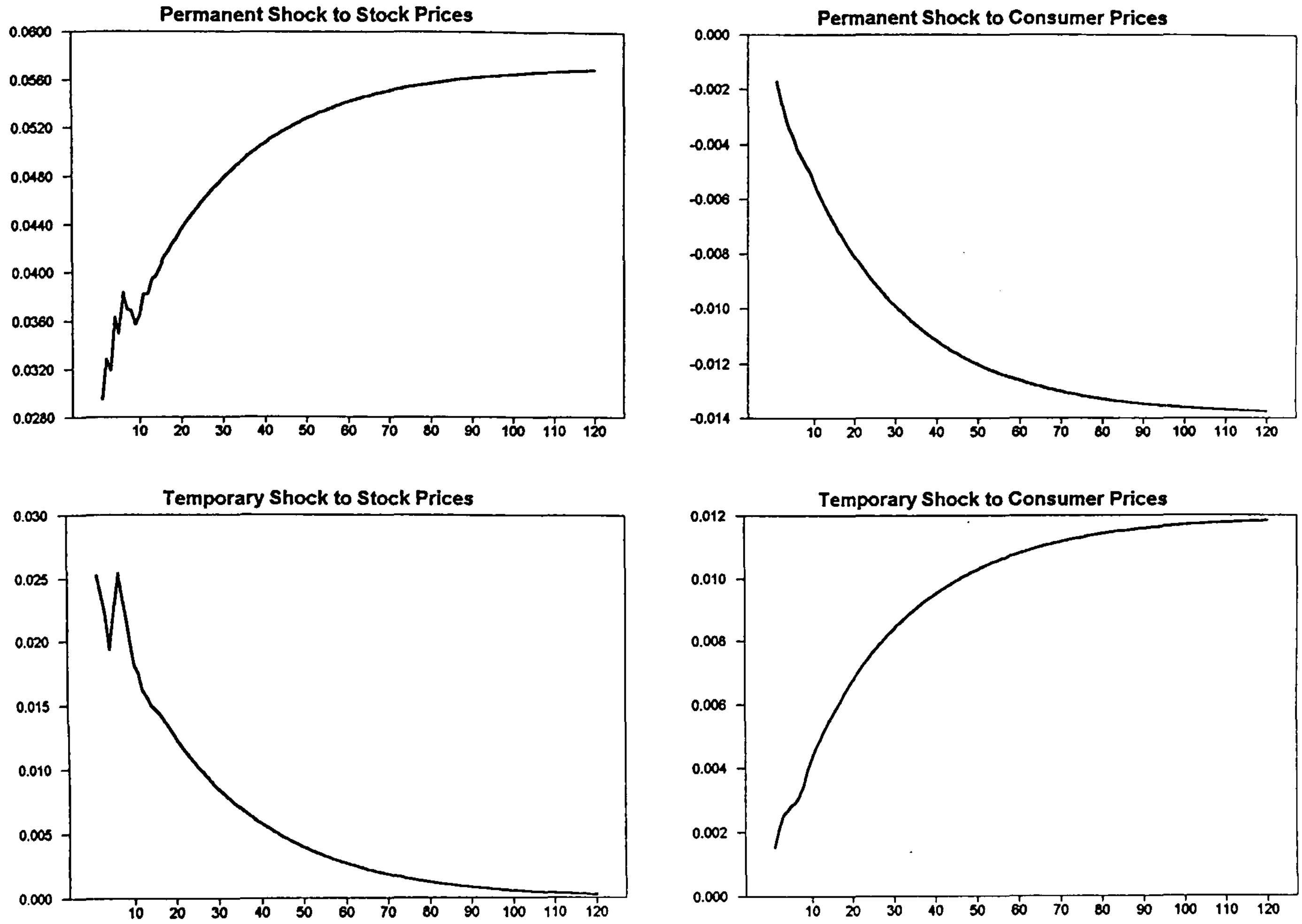


Figure 5.6: Components of Real Stock Prices

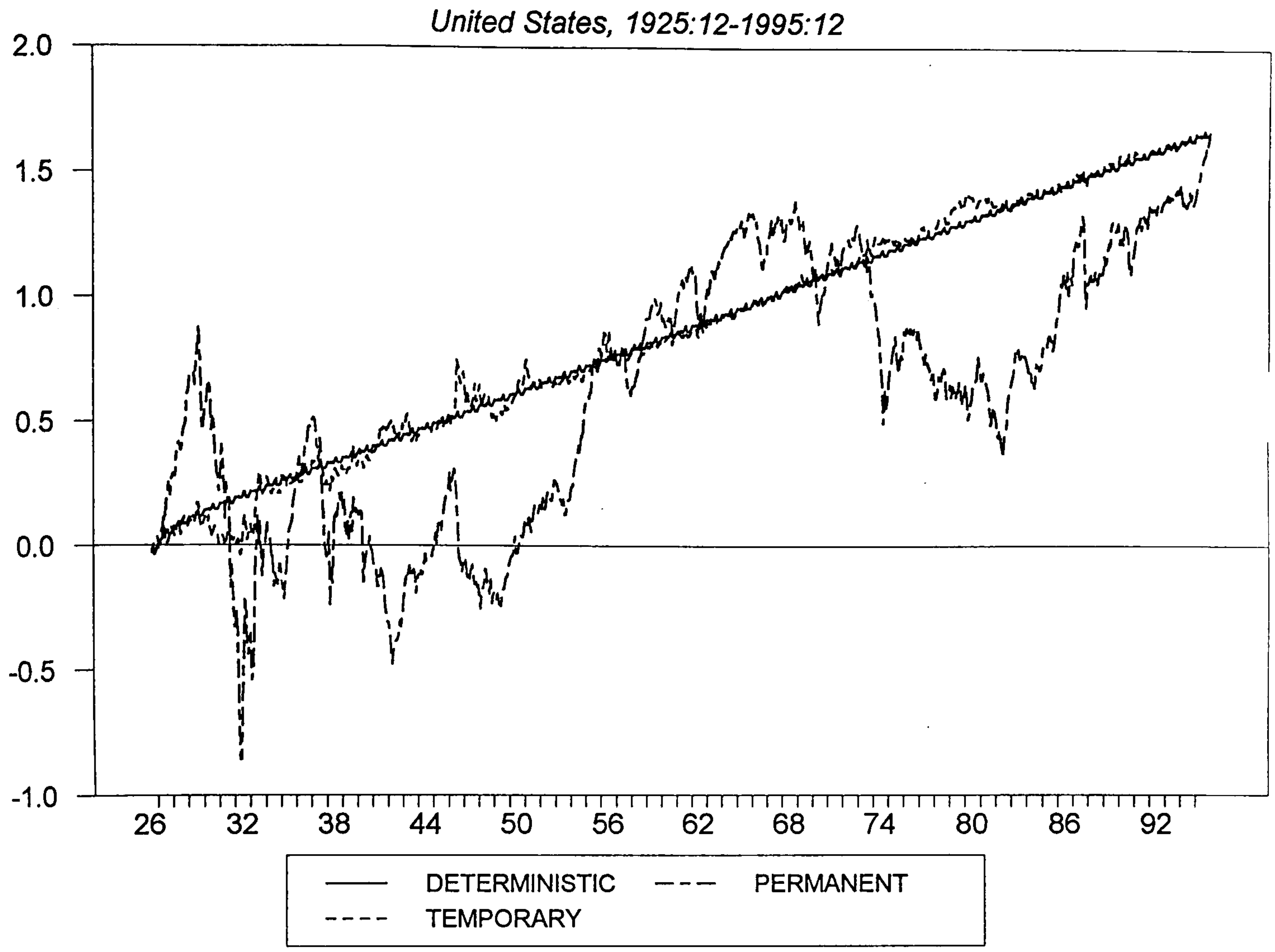


Figure 5.7: Components of Real Stock Prices

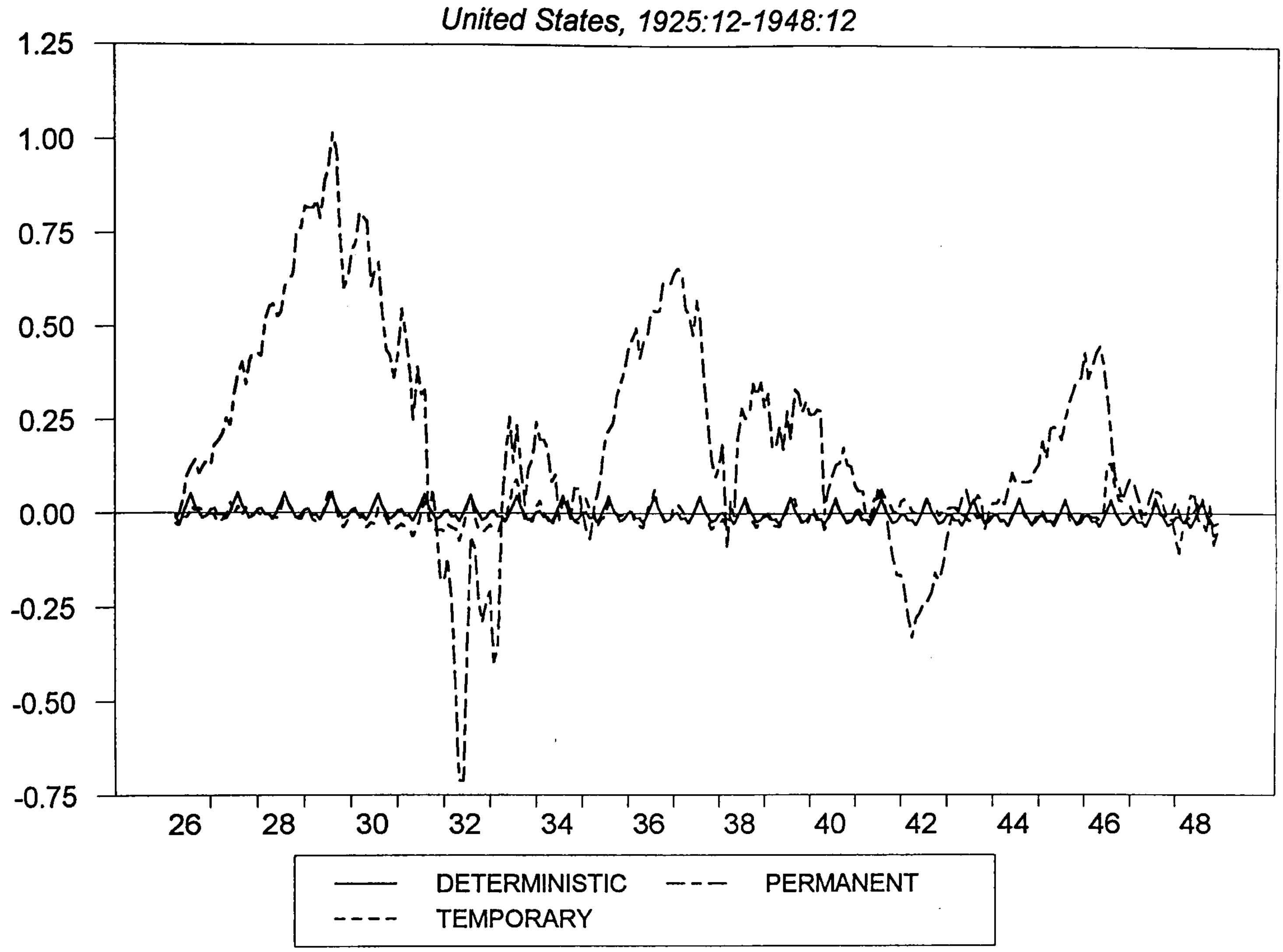
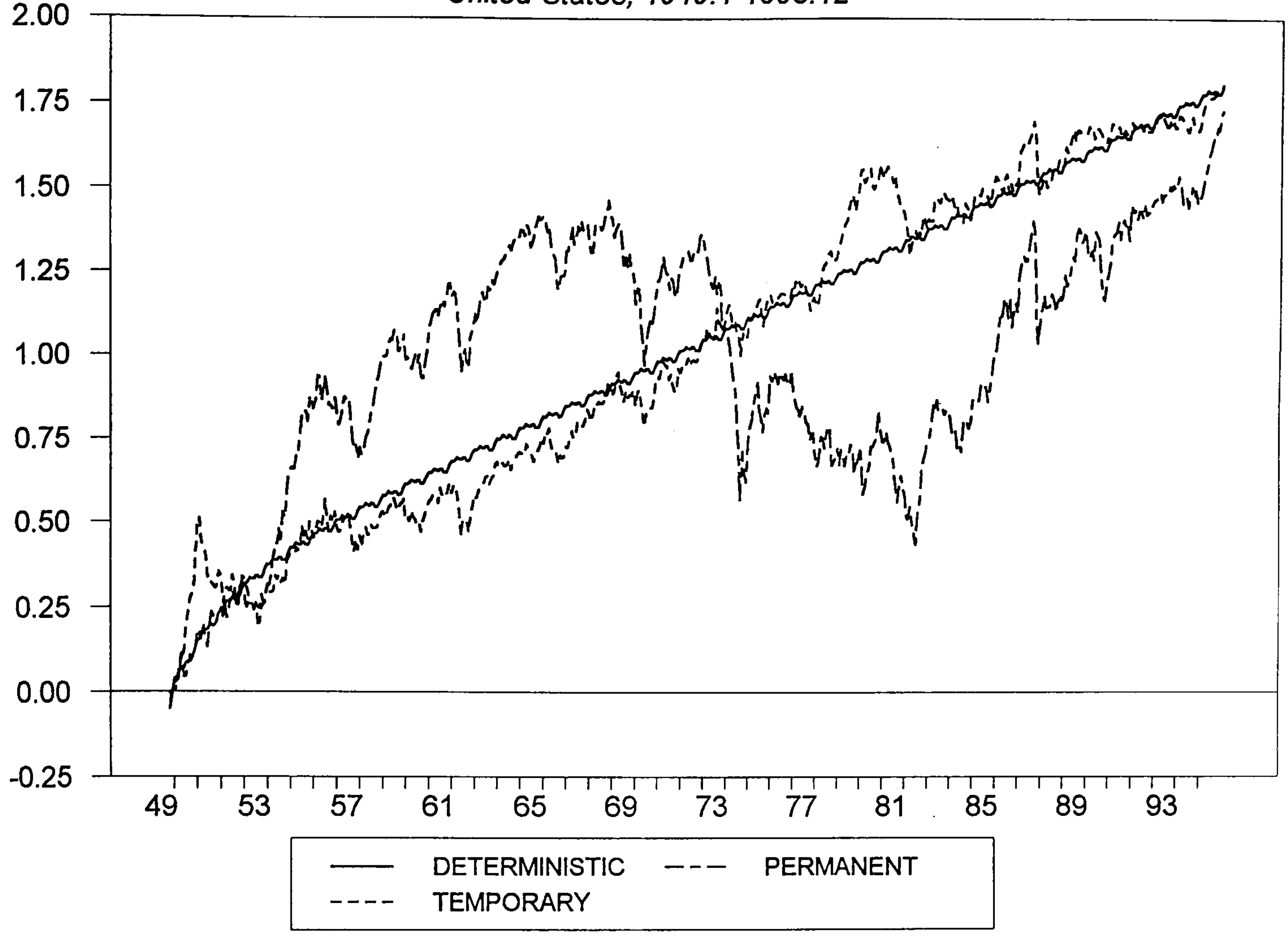


Figure 5.8: Components of Real Stock Prices

United States, 1949:1-1995:12



5.4 Forecast Error Variance Decomposition

Table 5.7 reports the forecast error variance decompositions of real stock prices and consumer prices to the contributions of permanent innovations and temporary innovations. At the one-month horizon, over 43 percent of the forecast error variance in real stock prices is due to temporary (aggregate demand) innovations, for the period 1949:1-1995:12. The forecast error variance increases to over 44 percent at the twelve-month horizon.

Since there are a number of studies that have examined the forecast error variance in consumer prices (for the post-war period) it is worth considering whether the results are consistent with previous studies (Bayoumi and Taylor, 1995; Gamber, 1996). For example, Bayoumi and Taylor (1995) report that in the 1980s (1970s), for the US, 53 (38) percent of the variance in consumer prices is explained by temporary (aggregate demand) shocks. We report broadly similar findings that 46 percent of the variation in consumer price movements is due to temporary shocks.

The size of this mean-reverting (temporary) component in real US stock prices is similar to that of Fama and French (1988a) and also consistent with other recent studies that have examined permanent and temporary components of stock prices (Poterba and Summers, 1988; Cochrane and Sbordone, 1988; Cochrane, 1994; Lee, 1995). Cochrane (1994), for example, using a variant of the multivariate generalization of the Beveridge-Nelson decomposition applied to annual US stock price data for the period 1927-88, finds that 57 percent of the stock price variance error is due to temporary shocks. Lee (1995) reports a similar finding.

As indicated by the cumulative impulse response functions, if we include the 1925:12-1948:12 period in the analysis the forecast error variance in stock prices due to temporary shocks falls to 11 percent. Furthermore, for the first sub-period the temporary component only explains less than 4 percent of the variation in stock price movements.

It is important to bear in mind that the mean-reverting component that we have estimated is derived as the response of real stock prices to aggregate demand disturbances. Moreover, the response of real stock prices to aggregate supply disturbances may to some degree be mean reverting. Thus the above analysis strongly supports the hypothesis that stock prices are mean reverting.

The estimated size of the mean-reverting component is not, however, sufficient to determine its empirical importance. As with the variance-ratio test, a more pertinent question is whether the mean-reverting component is statistically significant. For example - as noted in Chapter 2, section 2.3 - variance-ratio tests tend to indicate the presence of mean reversion while statistical testing based on these methodologies tend to be unable to reject the hypothesis of no mean reversion because of the large (and biased) standard errors (Richardson and Stock, 1989). For this reason the presence or absence of mean reversion in stock prices tends to be argued on the basis of the size of the variance-ratio test and the size of the temporary component.

Table 5.7: Forecast Error Variance Decomposition

Percentage of Variance Due to Temporary Shocks:

	Full Period 1925:12-1995:12		First Sub-Period 1925:12-1948:12		Second Sub-Period 1949:1-1995:12	
Horizon (months)	Consumer Prices	Stock Prices	Consumer Prices	Stock Prices	Consumer Prices	Stock Prices
1	86.69	10.63	96.41	3.49	43.87	43.66
2	87.83	10.57	96.91	3.47	42.83	43.45
3	87.99	10.65	94.86	3.57	42.37	43.49
4	88.31	11.64	94.94	3.90	41.31	43.24
5	88.80	11.66	95.11	3.96	40.98	43.45
6	88.71	11.75	95.16	3.97	40.01	43.49
12	89.54	11.90	95.25	3.99	42.69	44.17
24	89.92	11.94	95.25	3.99	45.46	44.20
36	89.99	11.95	95.25	3.99	46.12	44.21

Percentage of Variance Due to Permanent Shocks:

	Full Period 1925:12-1995:12		First Sub-Period 1925:12-1948:12		Second Sub-Period 1949:1-1995:12	
Horizon (months)	Consumer Prices	Stock Prices	Consumer Prices	Stock Prices	Consumer Prices	Stock Prices
1	13.31	89.37	3.59	96.51	56.13	56.34
2	12.17	89.43	3.09	96.53	57.17	56.55
3	12.01	89.35	5.14	96.43	57.63	56.51
4	11.69	88.36	5.06	96.10	58.69	56.76
5	11.20	88.34	4.89	96.04	59.02	56.55
6	11.29	88.25	4.84	96.03	59.99	56.51
12	10.46	88.10	4.75	96.01	57.31	55.83
24	10.08	88.06	4.75	96.01	54.54	55.80
36	10.01	88.05	4.75	96.01	53.88	55.79

5.5 The Statistical Significance of the Temporary Component

In the VAR decomposition, by construction, $x_t = [(1-L)q_t \;\; (1-L)p_t]$ is composed of three components: the permanent component, $x_{P,t}$, the temporary component, $x_{T,t}$, and the deterministic (trend and seasonal) component, $x_{D,t}$:

$$(5.1) \qquad x_t \equiv x_{T,t} + x_{P,t} + x_{D,t}$$

Since these three components are by construction orthogonal, the t-statistics of the slope coefficient resulting a least squares projection of the change in real stock prices onto each of these components in turn is a test of the significance of each component in explaining the variability of real stock prices. Therefore, regressing $(1-l)q_t$ onto $q_{T,t}$ provides a test of the statistical significance of the temporary component. The R^2s associated with each least squares regression estimate the proportion of total variation in real stock returns explained by each component. Furthermore, given the orthogonality of the three components, the R^2s from the least squares regressions must add up to unity.

Table 5.8 reports that the temporary (or mean-reverting) component is in fact statistically significant at standard significance levels for real stock prices. Furthermore, the reported R^2s are consistent with the forecast error variance decomposition.

Estimating similar t-statistics and R^2s for quarterly data produces t-statistics that are significantly different from zero, and at similar levels of significance as the monthly data reports. The R^2s indicate a slightly higher temporary component of the magnitude of 49 percent for the 1949:1-1992:12 period, 8 percent for the full period and 2 percent for the first sub-period. The R^2s are consistent with the forecast error variance decomposition. A detailed account of the quarterly data findings are provided in Chapter 6.

The above findings are conditional on the orthogonality of the shocks to stock prices. This can easily be empirically tested by regressing one shock on the other shock - for example, for the 1949:1-1995:12,

$$
\begin{array}{lll}
q_{T,t} = -0.0028\, q_{P,t} & & R^2 = 0.0000 \\
\qquad\quad (0.0367) & & SSE = 0.3832 \\
\qquad\quad [-0.0765] & & DW = 2.0501
\end{array}
$$

The R^2 of zero indicates that the temporary shock to real stock prices is uncorrelated with the permanent shock to real stock prices. Similar results are found for the full sample period and the first sub-periods.

Table 5.8: t-Test of Permanent, Temporary and Deterministic Components in Real Stock Prices

Full Period 1925:12-1995:12	(a)	$(1-L)q_t = 1.01\ q_{T,t}$ (0.10) [10.61]	$R^2 = 0.12$ SSE=2.41 DW=1.81
	(b)	$(1-L)q_t = 1.00\ q_{P,t}$ (0.01) [71.18]	$R^2 = 0.86$ SSE=0.39 DW=1.99
	(c)	$(1-L)q_t = 1.01\ q_{D,t}$ (0.22) [4.71]	$R^2 = 0.02$ SSE=2.67 DW=1.84
First Sub-Period 1925:12-1948:12	(a)	$(1-L)q_t = 1.00\ q_{T,t}$ (0.30) [3.32]	$R^2 = 0.04$ SSE=1.73 DW=1.80
	(b)	$(1-L)q_t = 1.00\ q_{P,t}$ (0.02) [52.25]	$R^2 = 0.91$ SSE=0.16 DW=1.78
	(c)	$(1-L)q_t = 1.00\ q_{D,t}$ (0.26) [3.90]	$R^2 = 0.05$ SSE=1.71 DW=1.81
Second Sub-Period 1949:1-1995:12	(a)	$(1-L)q_t = 1.00\ q_{T,t}$ (0.05) [19.48]	$R^2 = 0.41$ SSE=0.55 DW=1.77
	(b)	$(1-L)q_t = 1.00\ q_{P,t}$ (0.04) [25.93]	$R^2 = 0.55$ SSE=0.42 DW=1.97
	(c)	$(1-L)q_t = 1.01\ q_{D,t}$ (0.20) [4.96]	$R^2 = 0.04$ SSE=0.89 DW=1.92

Notes: $q_{T,t}$ is the temporary component, $q_{P,t}$ is the permanent component, and $q_{D,t}$ the deterministic component. Estimation is by ordinary least squares. Figures in parentheses denote estimated standard errors. Figures in brackets denote standard t-statistics. DW denotes the standard Durbin-Watson statistic for serial correlation. R^2 is the coefficient of determination. SSE denotes sum of squared errors.

5.6 Conclusion

In this chapter we have sought to measure and test the significance of a mean-reverting component in real stock prices in the US, using a variant of the Blanchard-Quah (1989) decomposition to estimate the temporary and permanent components in real stock prices. The temporary and permanent innovations to real stock prices are related to aggregate macroeconomic demand and supply innovations, respectively. Since the response of real stock prices to temporary innovations is zero, the temporary component is mean-reverting. Thus the procedure isolates a mean-reverting component in stock prices. If this mean-reverting component is significant then we can reject the random walk hypothesis in favour of mean-reversion hypothesis.

Our empirical results supports the mean-reversion hypothesis that stock prices are not pure random walks. Thus real returns are to some extent predictable. We estimate that the mean-reverting component accounts for 44 percent of the variation of monthly real stock returns, and is statistically significant. We find that temporary innovations to real stock prices tend to be quite persistent, with a half-life of 18 months. Previous studies that have isolated the random walk component from the mean-reverting component (see for example, Fama and French, 1988a; Poterba and Summers, 1988) also find that stock prices have slowly decaying stationary components.

The results are also consistent with those of more recent studies who have used vector autoregressive techniques to decompose stock prices into their temporary and permanent components (Cochrane, 1994; Lee, 1995). Moreover, the results are not subject to the recent controversy associated with long return horizon analysis (Richardson and Stock, 1989; Cecchetti *et al.*, 1990; Kim *et al.*, 1991; Mankiw *et al.*, 1991; Richardson, 1993).

The association between a significant mean-reverting component and predictability of stock returns has several potential implications for the practical investor. First, the evidence of mean reversion implies that real stock returns are to some degree predictable. It is worth noting that stock returns are more strongly forecastable in the post-war period due to the high variability that surrounds the Great Depression and WW II period (Campbell, 1990, 1991: Cochrane, 1994). Second, in the presence of mean reversion, an investor with a relative risk aversion coefficient of less (greater) than unity will invest less (more) in equities as his investment horizon increases (Samuelson, 1991). Moreover, the presence of a mean-reverting component suggests using a portfolio strategy of going long in equities that have recently declined in value. The reason for the significant mean-reverting component in stock prices is not obviously clear, a plausible explanation is provided by noise traders in markets (De Long *et al.*, 1990). For a discussion on this issue see Chapter 2. However, it is market microstructure analysis that is likely to provide further insights into the explanation of mean reversion (O' Hara, 1995). Furthermore, this approach has necessarily limited itself to the study of linear (or, more precisely, log-linear) persistence in stock prices. Future research might profitably study the presence of predictable non-linearities in stock price behaviour - this is an issue that we take up in Chapters 10 and 11.[38]

[38]Tong (1990) reports evidence of non-linearity in a number of stock price series.

Chapter 6

A MULTI-COUNTRY ANALYSIS OF TEMPORARY AND PERMANENT COMPONENTS IN STOCK PRICES

6.1 Introduction

With the exception of a few studies that have tested the mean reversion hypothesis (Poterba and Summers, 1988; Cochran, DeFina and Mills, 1993; Frennberg and Hansson, 1993; Mills, 1991, 1995; Cochran and DeFina, 1995), markets other than the US have been neglected, principally because of the unavailability of high quality non-overlapping long time series for stock prices that traditional techniques require. Moreover only Poterba and Summers (1988) and Cochran *et al.* (1993) and Cochran and DeFina (1995) provide international evidence on stock price behaviour.

In this chapter we measure the size and significance of the temporary (or mean-reverting) and permanent components of real stock prices for sixteen stock markets. As in the last Chapter, we employ a multivariate time series technique based on the vector autoregressive representation of real stock prices and consumer prices - as outlined in Chapter 4, section 4.1 - to decompose the stock prices.[39] In this context, the temporary and permanent components of stock price movements are related to aggregate macroeconomics demand and supply disturbances. However, this section offers a much broader international evidence

[39]The technique employed can be viewed as a multivariate generalisation of the Beveridge-Nelson (1981) decomposition.

on the size of the mean-reverting component and predictability of stock prices than has been hitherto available. Furthermore, the interest in worldwide investing warrants information on markets other than the stock markets of US, UK and Japan. The results from a range of stock markets provides evidence on the time series properties of stock returns and allow more general inferences than do results on a single country.

6.2 Data and Summary Statistics

Quarterly data for sixteen countries were obtained from the International Monetary Fund's International Financial Statistics data base. The sample period is 1957i to 1995iv.[40] For the United States quarterly data were obtained from the Center for Research in Securities Prices (CRSP) for the 1925v to 1995v period. As is evident from studies by Shiller and Perron (1985) and others, in examining the persistent, low frequency properties of time series data, the *span* of the time series - in terms of years - is much more important than the number of observations *per se*.[41] Hence, in selecting our international data set on stock prices, we sought to satisfy two criteria: *consistency*, which required us to choose data of the same frequency and more or less the same sample period for each country; and overall time series *span*, which required us to seek out the longest samples. On this basis, we chose quarterly data on stock prices, since these were available for a number of countries on a continuous basis from as early as 1957.

The following countries were included in the study: Austria, Belgium, Canada, Finland, France, Germany, India, Italy, Japan, Netherlands, Norway, South Africa, Sweden, Switzerland, the UK and the US.

The data series of interest are the natural logarithm of the real stock price

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[40] Data was only available for the period 1957i - 1993iv for France; 1959i - 1995ii for Germany; and 1957ii - 1995iv for India.

[41] An intuitive discussion of this point is given in Davidson and MacKinnon (1993, ch. 20).

index, q_t, and the natural logarithm of the consumer price index p_t. The real stock price index is constructed using the consumer price index. The logarithm of the real stock price indices, rebased so that the average price for 1990 is unity, are presented in Figure 6.1.

Table 6.1 reports summary statistics on the series of interest. The sample autocorrelations reveal some degree of persistence and suggest that the series are nonstationary. The impression that the series in question are realizations of non-stationary processes is confirmed by the standard unit root tests reported in Table 6.2. The sequential procedure employed in testing for unit roots follows Dickey and Pantula (1987) in order to ensure that only one unit root is present in the series. The unit root tests are the augmented Dickey-Fuller (ADF) test and the Phillips-Perron Z_t (PP) test for the null hypothesis that the series in question is I(1) (Dickey and Fuller, 1979, 1981; Perron, 1988). Consistent with the relevant literature, for each country, the real stock price series appear to be realizations of first-difference stationary or I(1) processes.

As a test for cointegration, the results of the ADF (μ_t) test for a unit root in the least squares residual from a regression of p_t onto q_t and a constant are reported in Table 6.2b (final column). For all countries the null hypothesis of no cointegration cannot be rejected.

Table 6.1: Summary Statistics

(a) Real Stock Returns

	Mean	S.d.	Autocorrelation, ρ(k) ρ(1)	ρ(2)	ρ(3)	ρ(4)	ρ(5)	ρ(6)
Austria	0.35	9.53	0.22*	0.21*	0.11	0.07	-0.08	-0.07
Belgium	-0.28	7.76	-0.01	0.05	0.04	0.15	-0.15	-0.01
Canada	0.21	7.91	0.16	-0.05	-0.08	-0.13	-0.05	-0.11
Finland	0.82	10.00	0.18*	0.17*	0.29*	0.26*	-0.07	-0.06
France	0.17	8.73	0.31*	-0.03	0.03	0.01	-0.11	-0.16
Germany	0.43	9.25	0.12	-0.01	0.18*	0.06	-0.16	-0.01
India	0.27	9.41	0.07	0.17*	-0.03	-0.05	-0.23*	-0.01
Italy	-0.41	12.95	0.02	0.17*	0.11	0.24*	-0.22*	0.00
Japan	1.06	8.54	0.24*	-0.01	0.12	0.02	-0.02	0.06
Netherlands	0.49	8.70	0.07	-0.07	0.17*	0.17*	-0.13	-0.10
Norway	0.19	14.46	-0.17*	0.00	0.03	0.10	-0.14	-0.15
S. Africa	0.33	10.23	0.08	0.02	0.08	-0.01	-0.09	-0.05
Sweden	1.10	9.76	0.06	0.04	0.10	0.01	-0.14	-0.20*
Switzerland	0.29	9.68	-0.03	0.03	0.28*	0.06	-0.13	0.12
UK	0.60	10.13	0.11	-0.05	0.04	0.01	-0.10	-0.06
US(57i-95iv)	0.60	8.04	0.11	-0.13	-0.05	-0.03	-0.02	-0.09
US(25iv-95iv)	0.63	11.04	-0.05	0.00	0.16	-0.17*	0.01	0.01
US(25iv-56iv)	0.72	13.97	-0.12	0.05	0.25*	-0.23*	0.02	0.06

(b) Inflation

	Mean	S.d.	Autocorrelation, ρ(k) ρ(1)	ρ(2)	ρ(3)	ρ(4)	ρ(5)	ρ(6)
Austria	0.98	1.46	0.28*	0.08	-0.21*	0.55*	-0.07	-0.04
Belgium	1.04	0.91	0.49*	0.57*	0.57*	0.51*	0.39*	0.54*
Canada	1.16	0.91	0.68*	0.59*	0.64*	0.67*	0.58*	0.51*
Finland	1.58	1.30	0.46*	0.49*	0.37*	0.53*	0.31*	0.36*
France	1.54	1.09	0.70*	0.49*	0.43*	0.53*	0.43*	0.40*
Germany	0.82	0.72	0.23*	-0.05	0.30*	0.63*	0.19	-0.09
India	1.84	2.52	0.28*	-0.21*	0.17	0.43*	-0.02	-0.48*
Italy	1.89	1.52	0.78*	0.71*	0.71*	0.66*	0.61*	0.61*
Japan	1.12	1.32	0.46*	0.44*	0.42*	0.46*	0.27*	0.31*
Netherlands	1.03	1.21	0.09	0.15	0.21*	0.44*	-0.01	0.14
Norway	1.40	1.22	0.22*	0.32*	0.15	0.44*	0.11	0.26*
S. Africa	2.12	1.43	0.60*	0.72*	0.63*	0.74*	0.60*	0.65*
Sweden	1.50	1.22	0.14	0.33*	0.21*	0.44*	0.10	0.21*
Switzerland	0.87	0.83	0.29*	0.26*	0.30*	0.42*	0.15	0.18*
U.K.	1.65	1.57	0.49*	0.52*	0.38*	0.62*	0.32*	0.38*
US(57i-95iv)	1.10	0.85	0.69*	0.63*	0.66*	0.64*	0.52*	0.44*
US(25iv-95iv)	0.77	1.40	0.57*	0.45*	0.46*	0.47*	0.33*	0.21*
US(25iv-56iv)	0.35	1.79	0.50*	0.35*	0.35*	0.37*	0.21*	0.07

Notes: The sample period is 1957i-1995iv; also see text for slight deviations from this sample period. The mean and standard deviation (S.d.) are expressed in percentage terms. ρ(k) is the autocorrelation between Δq_t and Δp_{t-k} and for inflation, between Δp_t and Δp_{t-k}. Real stock returns are equal to Δq_t, where q_t is the natural logarithm of the real stock price index and Δ denotes the first difference. Inflation is equal to Δp_t, where p_t is the natural logarithm of the consumer price index. An asterisk denotes the sample autocorrelation is at least two standard deviations to the left or to the right of its expected value under the hypothesis that the true autocorrelation is zero.

Table 6.2: Unit Root and Cointegration Tests

(a) Phillips Perron Test

	PP			
	p_t	q_t	Δp_t	Δq_t
Austria	-0.36	-1.80	-16.34	-9.93
Belgium	0.28	-1.67	-6.77	-12.46
Canada	0.99	-2.85	-4.95	-10.41
Finland	-0.78	-0.49	-7.33	-10.20
France	-0.61	-1.28	-5.29	-8.97
Germany	-0.33	-2.58	-9.32	-10.86
India	1.18	-1.02	-9.22	-11.48
Italy	1.64	-1.38	-4.08	-12.20
Japan	-2.07	-1.18	-7.30	-9.75
Netherlands	-1.68	-0.93	-11.59	-11.60
Norway	0.36	-1.60	-10.02	-14.81
S. Africa	7.70	-2.07	-9.04	-11.40
Sweden	1.15	-0.47	-10.87	-11.68
Switzerland	-0.26	-1.47	-10.04	-12.83
U.K.	0.43	-1.70	-7.10	-11.14
US(57i-95iv)	1.33	-1.36	-4.82	-11.02
US(25iv-95iv)	2.62	-1.43	-8.77	-17.56
US(25iv-56iv)	0.45	-2.26	-6.49	-12.37

(b) Augmented Dickey Fuller Tests

	ADF				Coint.
	p_t	q_t	Δp_t	Δq_t	μ_t
Austria	-0.45	-2.08	-2.98	-6.45	-0.21
Belgium	-0.03	-1.41	-3.80	-4.96	-0.32
Canada	0.21	-2.55	-3.68	-6.29	-0.15
Finland	-0.67	-1.07	-3.49	-4.59	-2.19
France	0.32	-1.76	-2.91	-8.14	0.55
Germany	-0.49	-1.70	-4.56	-5.24	-0.32
India	0.95	-1.07	-3.79	-6.94	-0.19
Italy	0.30	-1.57	-3.08	-5.54	-1.31
Japan	-1.54	-1.44	-3.55	-8.04	-1.76
Netherlands	-0.98	-0.98	-4.89	-9.02	-0.44
Norway	-0.16	-1.38	-4.87	-9.69	0.63
S. Africa	4.55	-2.18	-4.21	-8.14	0.31
Sweden	0.53	-0.50	-4.30	-8.13	-1.68
Switzerland	-0.76	-1.88	-3.22	-4.31	-0.04
U.K.	-0.18	-1.79	-3.63	-8.74	-0.62
US(57i-95iv)	0.50	-1.45	-3.49	-9.45	-0.22
US(25iv-95iv)	0.72	-1.30	-4.17	-7.65	-1.61
US(25iv-56iv)	-0.44	-2.39	-3.12	-12.37	-0.74

Notes: The sample period is 1957i-1995iv. See Table 6.1 for a definition of the variables. μ_t is the OLS regression of p_t onto q and a constant. The unit root tests are the Phillips-Perron (PP), Z and the augmented Dickey-Fuller (ADF) test statistic for the null hypothesis that the series is difference stationary (Dickey and Fuller, 1979, 1981; Perron, 1988). The lag truncation was chosen using the Ljung-Box Q-statistic to ensure whiteness of the residuals. The unit root test of Δp_t for S. Africa includes a time trend. For a 5% significance level the critical ADF and PP is -2.89 and (see, Fuller, 1976, p.373). The cointegration test, μ_t, is the ADF test; for a 5% significance level the critical value is -3.17 (see Fuller, 1976, pp. 371-3; Engle and Granger, 1987).

Figure 6.1a: Real Stock Prices

1957:1 - 1995:4

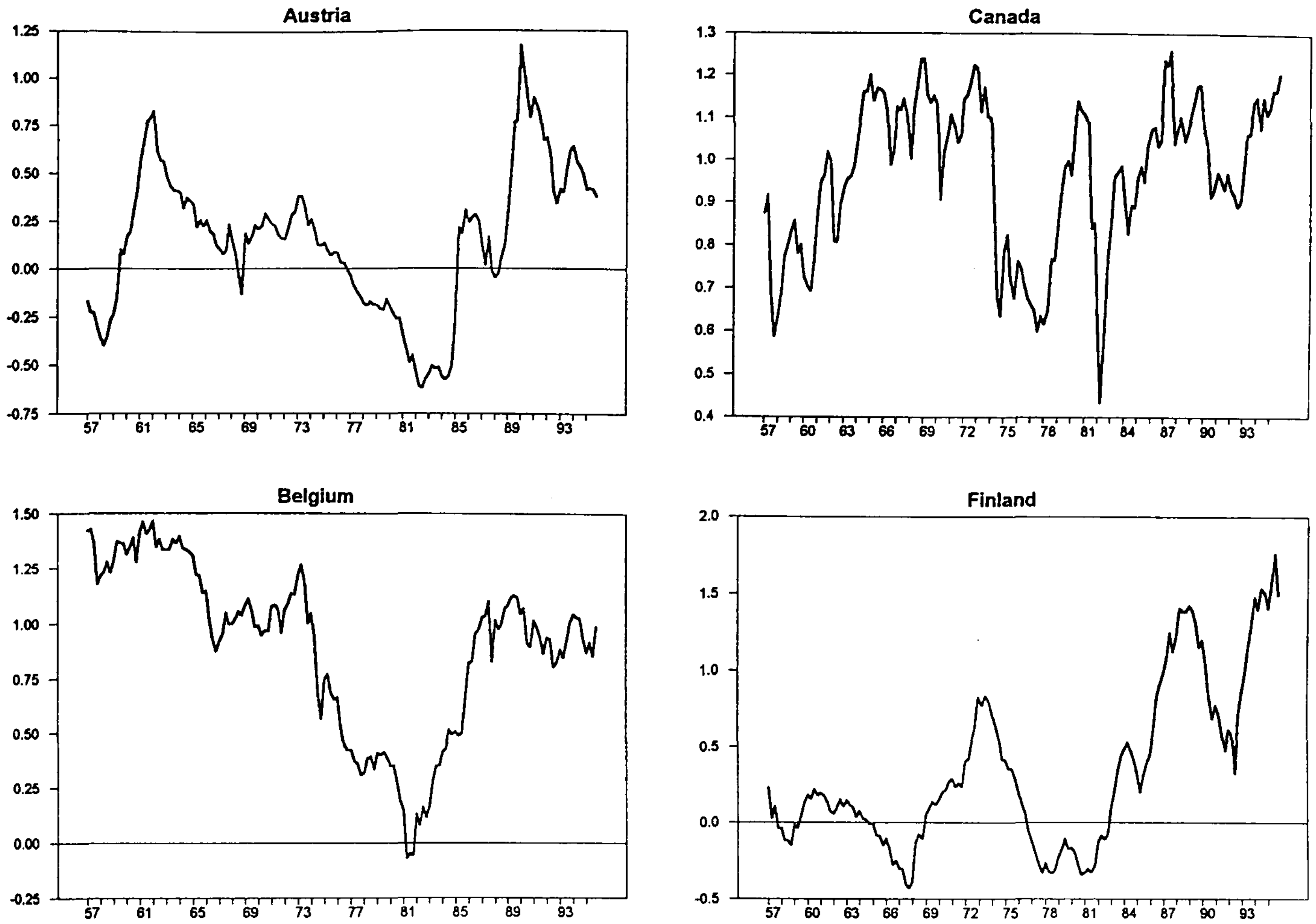


Figure 6.1b: Real Stock Prices

1957:1 - 1995:4

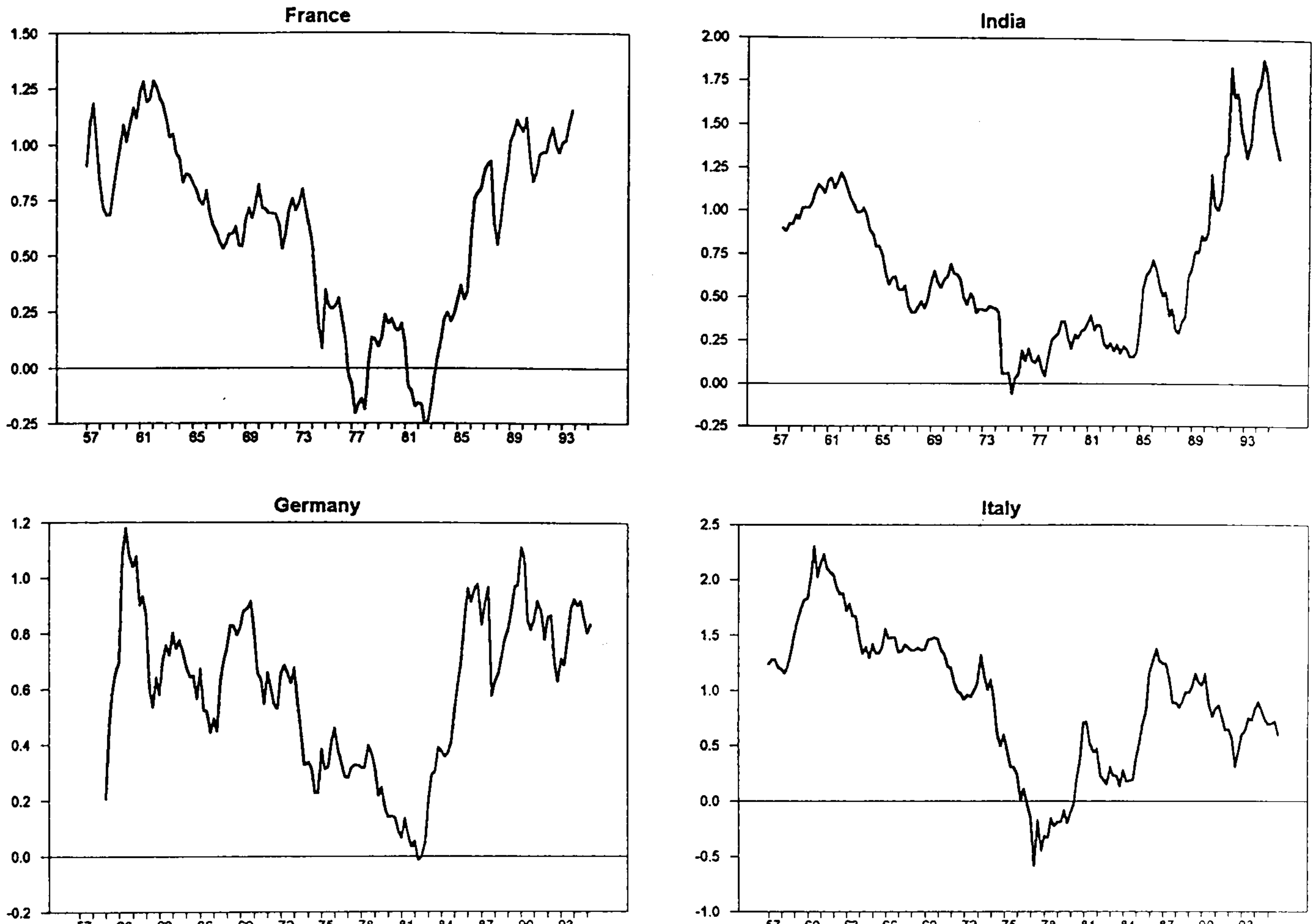
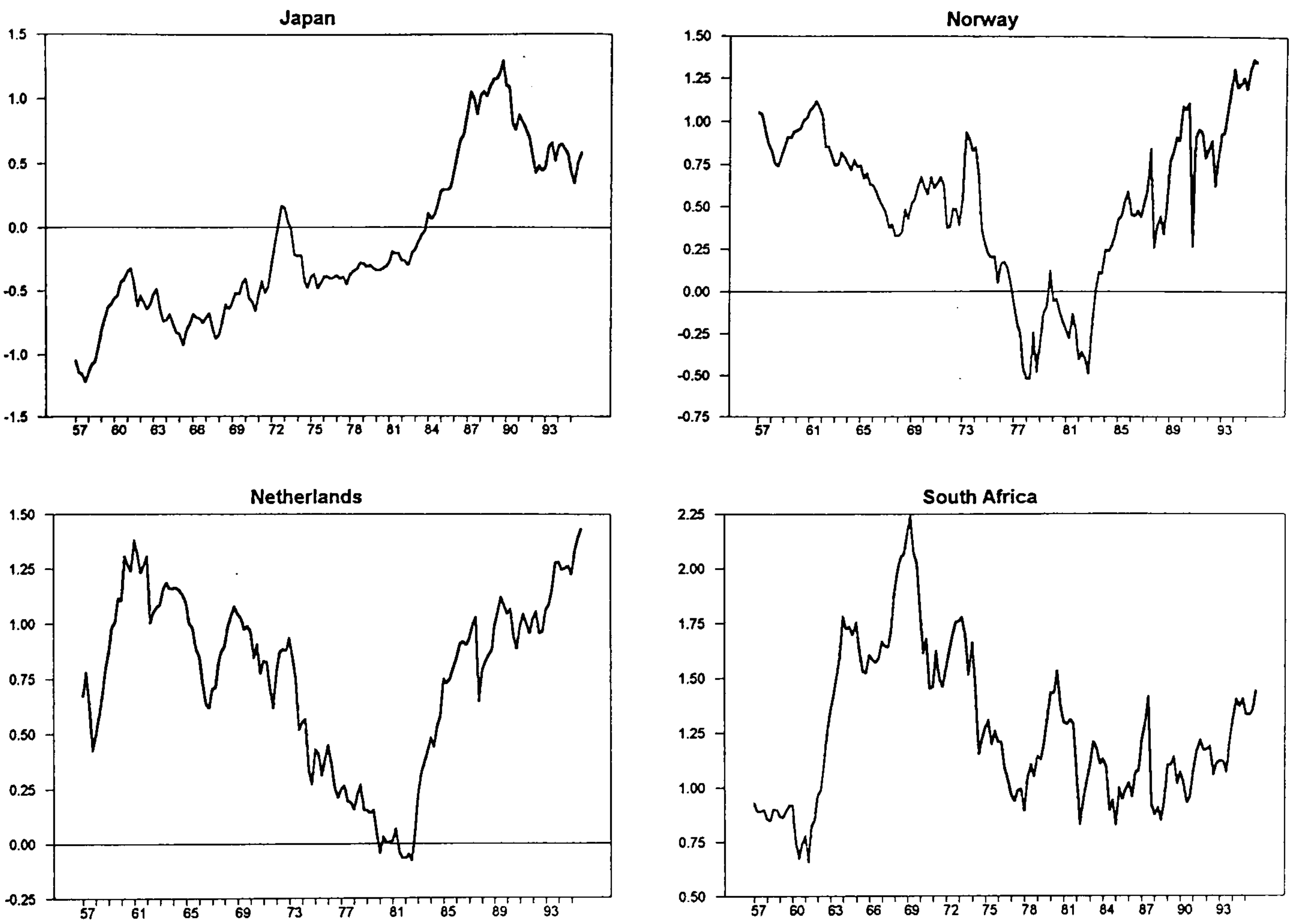


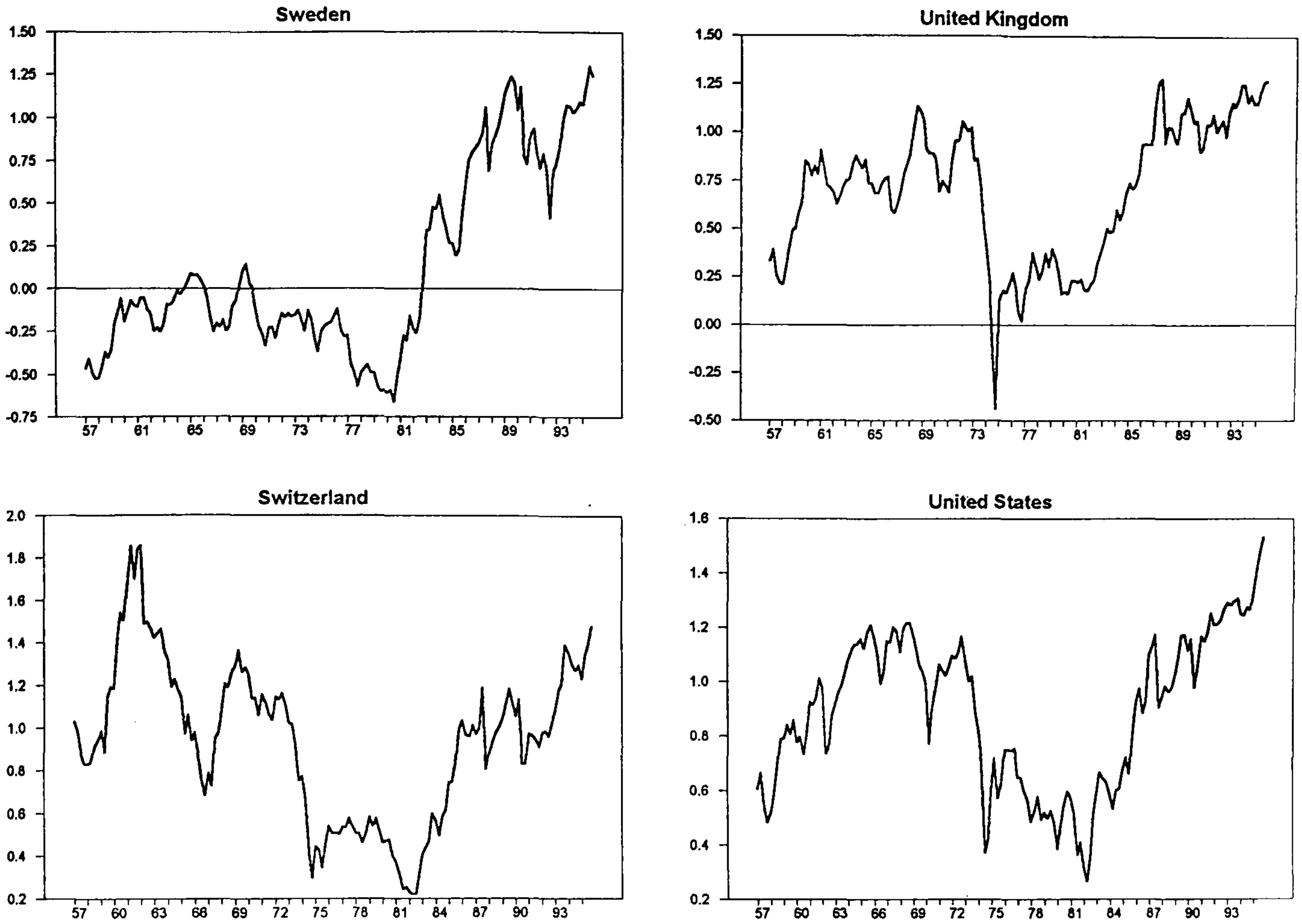
Figure 6.1c: Real Stock Prices

1957:1 - 1995:4



[illegible].1d: Real Stock Prices

1957:1 - 1995:4



6.3 Decomposing Stock Price Movements: Estimating the Temporary and Permanent Component by VAR Analysis

A vector autoregressive representation of $[(1\text{-L})q_t \;\; (1\text{-L})p]'$ was estimated[42] preliminary to effecting the decomposition. The lag length for the VAR was chosen as follows. First, using the Bayes Information Criterion (BIC), an initial lag length was determined.[43] Second, using the Ljung-Box Q-statistic we tested for the whiteness of the residuals and the lag depth was increased (if necessary) until they were approximately white noise - for each country, the lag length used for the VAR is reported in the final column of Table 6.3. The Akaike Information Criterion (AIC) is also reported for comparison purposes.

Using the A(0) matrix, estimated from the VAR parameters and the covariance matrix of VAR residuals (not reported), we decomposed real stock prices into a temporary component and permanent component. The generated cumulative impulse response functions for stock prices and consumer prices, are presented in Figure 6.2. These illustrate the dynamic effects of a one unit (standard deviation) shock on the level of real stock prices and consumer prices.

The macro model imposes the qualitative restrictions - a permanent disturbance to real stock prices increases (in the short run and long run) stock

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[42] Seasonal dummies were included in the VAR.

[43] In a Monte Carlo analysis of alternative criteria to determine lag length of VARs, Lütkepohl (1985) favours the Schwarz-multivariate BIC criterion. Lütkepohl finds that the BIC criterion chooses the correct lag order most often and the resulting VAR models provide the best forecasts.

prices, whereas a temporary disturbance to stock prices increases real stock prices only in the short run, with zero long-run effect. A positive temporary shock to consumer prices increases consumer prices, whereas a positive permanent shock to consumer prices decreases consumer prices.

The temporary shock to real stock prices is persistent for a number of countries, most noticeably, Finland, Italy, Netherlands and South Africa (see Table 6.4 for measures of half-life of the temporary shock to real stock prices). Thus for these countries, even though the mean-reverting component may explain a large amount of the variation in stock price movements, it is difficult to detect it at high frequency, as it looks very much like a random walk component. The two larger markets, US and UK, reveal little persistence, as a temporary shock to real stock prices dies fairly fast - with a half-life of only 2 quarters - similar levels of persistence is found for France, Germany and Norway.

For the majority of countries, the effect of a permanent shock to real stock prices is for stock prices to rise continuously for around the first sixteen quarters and then to a large degree remain at (or around) that higher value. The exception is Norway, where real stock prices initially fall for the first three quarters and then rise. Furthermore, for Canada and the Netherlands, a permanent shock to real stock prices causes stock prices to continue to rise even after sixteen quarters.

Also for a number of countries (Finland, Japan, Netherlands and Switzerland) the final response of a permanent shock to real stock price is over twice the initial (one standard deviation) effect. Whereas, for France, Germany, India, Italy Norway, UK and US the final effect is that real stock prices are only slightly higher than their initial effect.

The response of consumer prices to temporary and permanent shocks is similar to what we found in the previous chapter - a positive temporary shock to consumer prices causes prices to rise and a positive permanent shock causes prices to fall. However, the dynamic effects of the temporary and permanent shocks varies slightly across the different countries - that is , although the direction of consumer prices is the same for all countries to a demand and supply disturbance, the dynamic response of consumer prices to a disturbance is country specific. This is consistent with other multi-country analysis (for example, Bayoumi and Taylor, 1995). For the majority of countries the dynamic effects of temporary (demand) and permanent (supply) shocks are largely over by about five years.

Table 6.3: Choice of Lag Length

	AIC	BIC	Preferred Length
Austria	4	4	5
Belgium	4	3	4
Canada	4	1	6
Finland	6	2	5
France	4	1	5
Germany	4	1	5
India	4	1	4
Italy	6	2	5
Japan	4	1	4
Netherlands	4	4	4
Norway	2	1	3
S. Africa	4	2	5
Sweden	3	2	3
Switzerland	5	1	5
UK	2	2	5
US(57i-95iv)	2	2	7
US(25iv-95iv)	4	1	3
US(25iv-56iv)	1	3	1

Notes: The Bayes Information Criterion (BIC) was initially used to determine the lag length. This lag length was tested for serial correlation using the Ljung-Box Q-statistic and the lag depth was increased (if necessary) until the residuals were approximately white noise. The lag depth resulting from the outcome of this procedure is the preferred length and is the actual lag length used in the VAR analysis. The Akaike Information Criterion (AIC) is given for comparison purposes. The sample period is 1957i-1995iv.

Table 6.4: Half-Life of a Temporary Shock to Real Stock Prices: Number of Quarters

Austria	7
Belgium	8
Canada	7
Finland	13
France	1
Germany	2
India	3
Italy	12
Japan	7
Netherlands	11
Norway	1
S. Africa	25
Sweden	8
Switzerland	6
UK	2
US	2

Notes: The sample period is 1957i-1995iv. See Figure 6.2 for a graphical illustration of the temporary shock to real stock prices for each of the 16 countries.

Figure 6.2a: Cumulative Impulse Response Functions

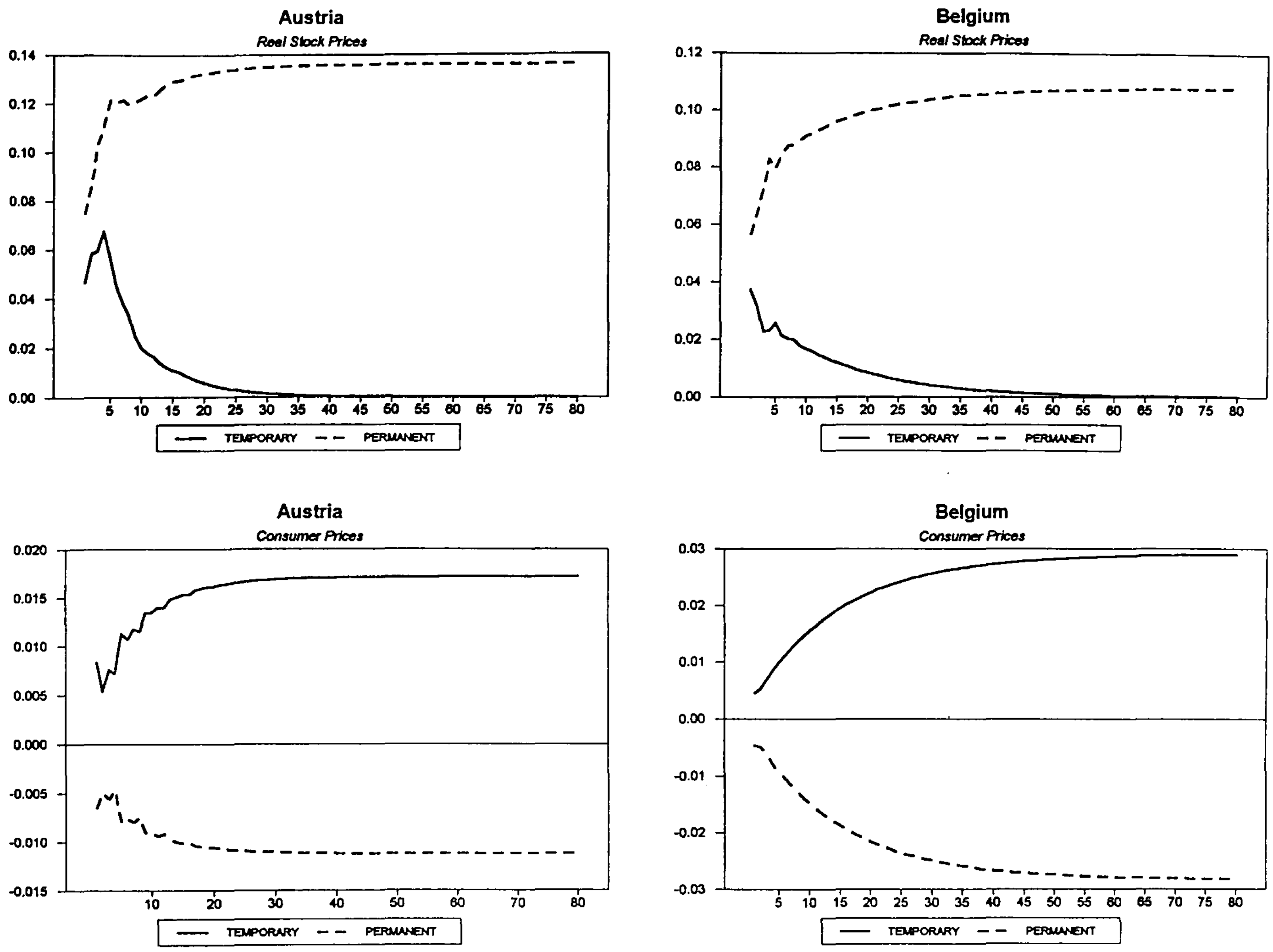


Figure 6.2b: Cumulative Impulse Response Functions

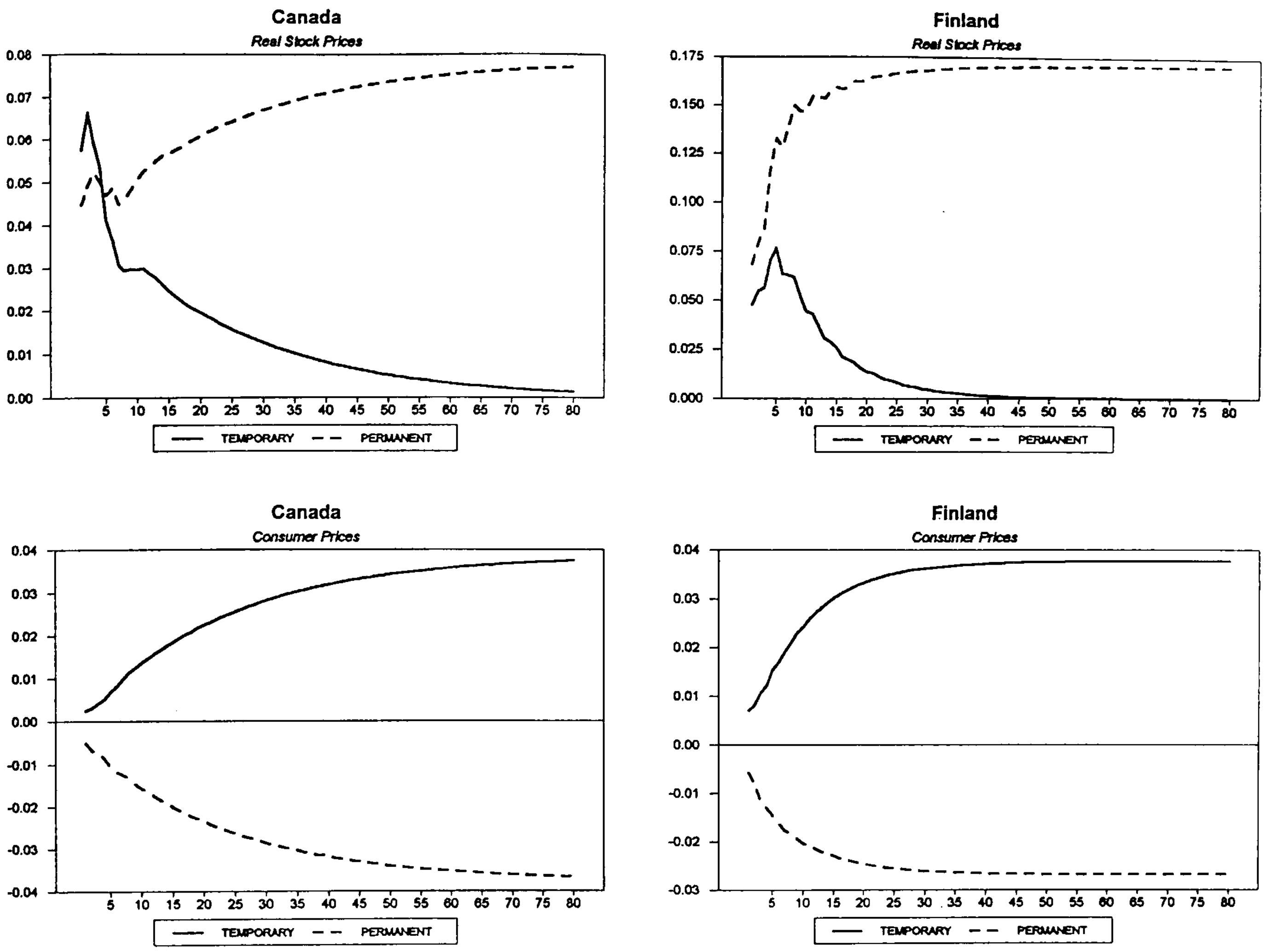


Figure 6.2c: Cumulative Impulse Response Functions

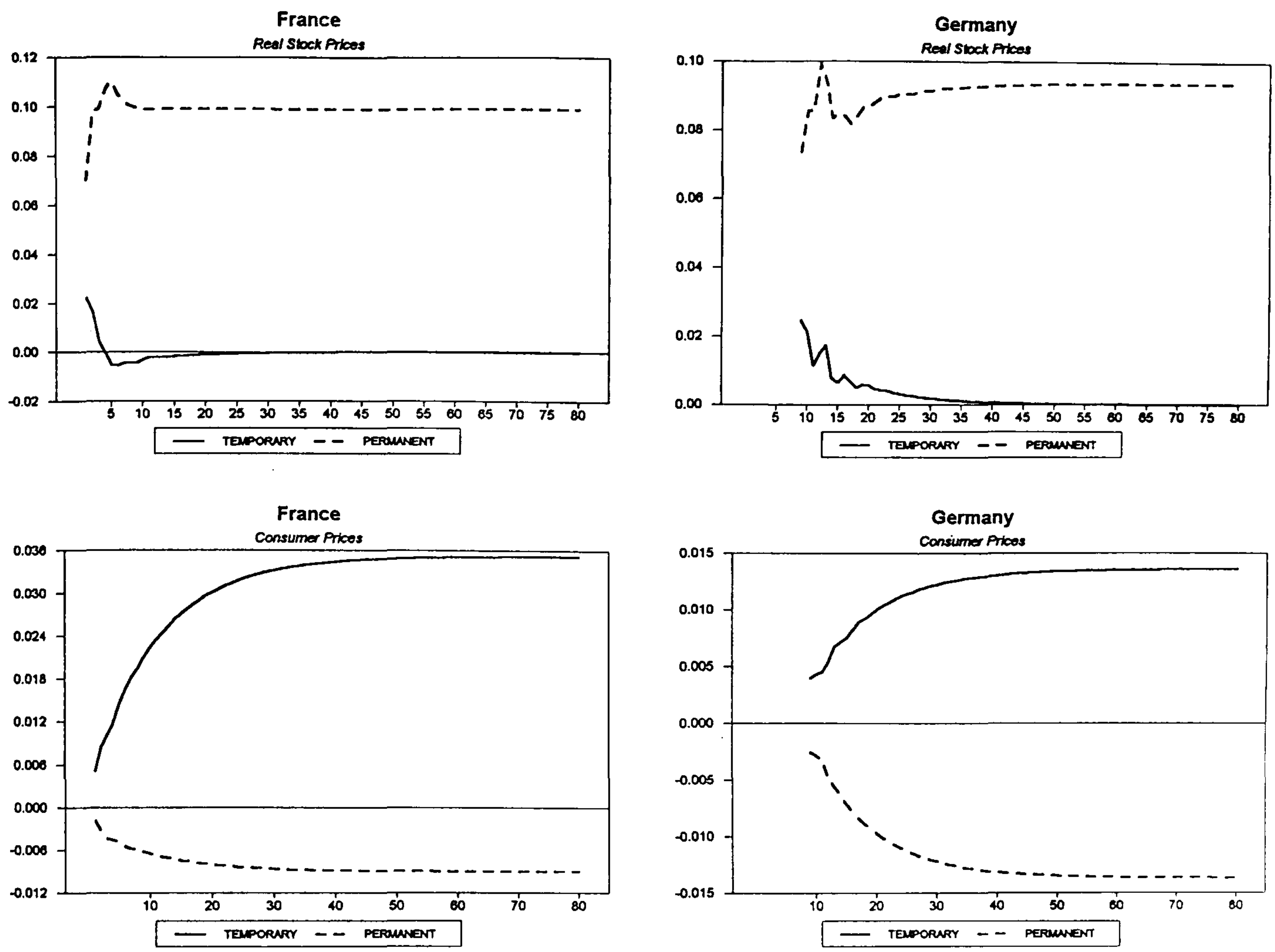


Figure 6.2d: Cumulative Impulse Response Functions

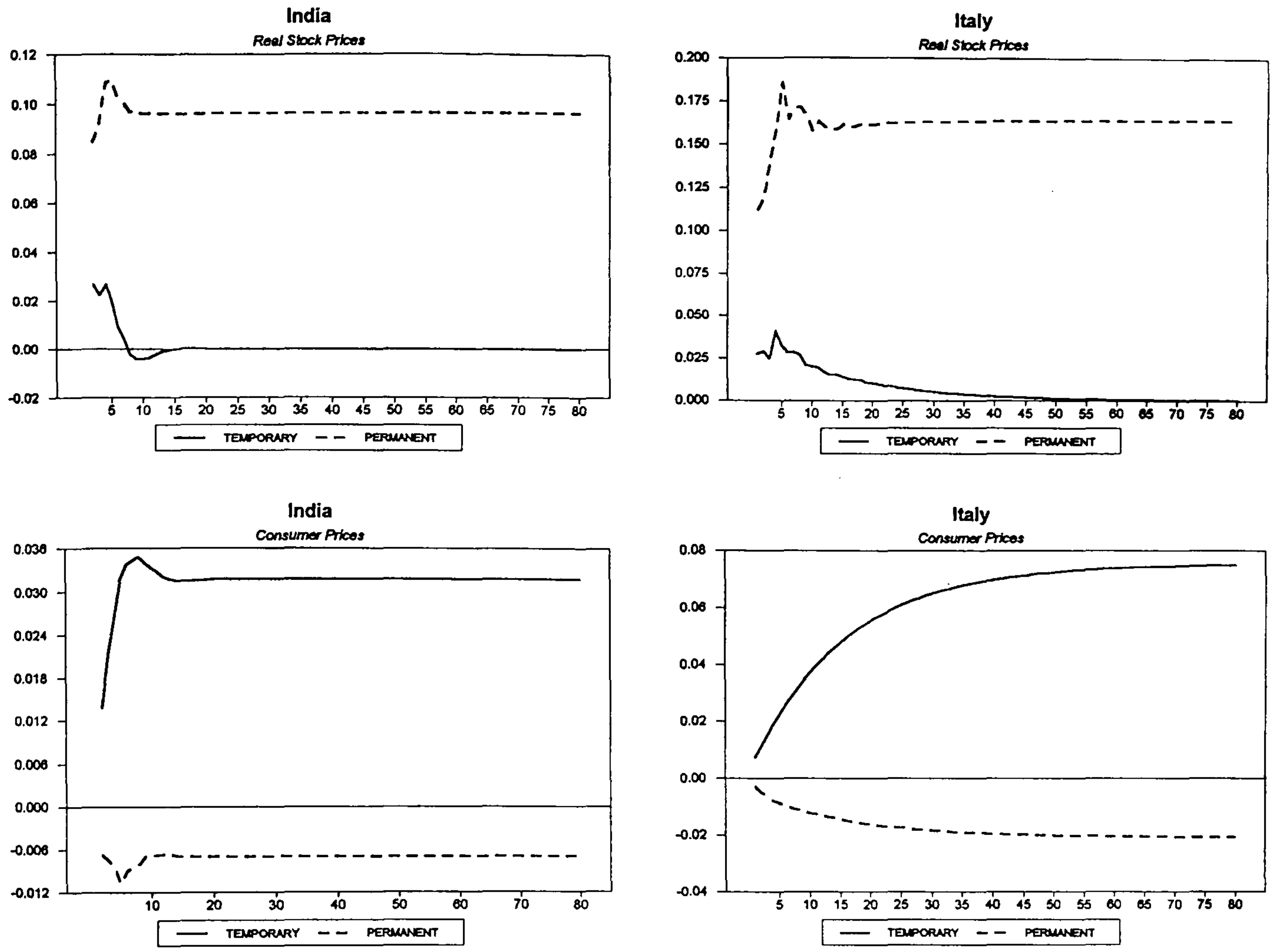


Figure 6.2e: Cumulative Impulse Response Functions

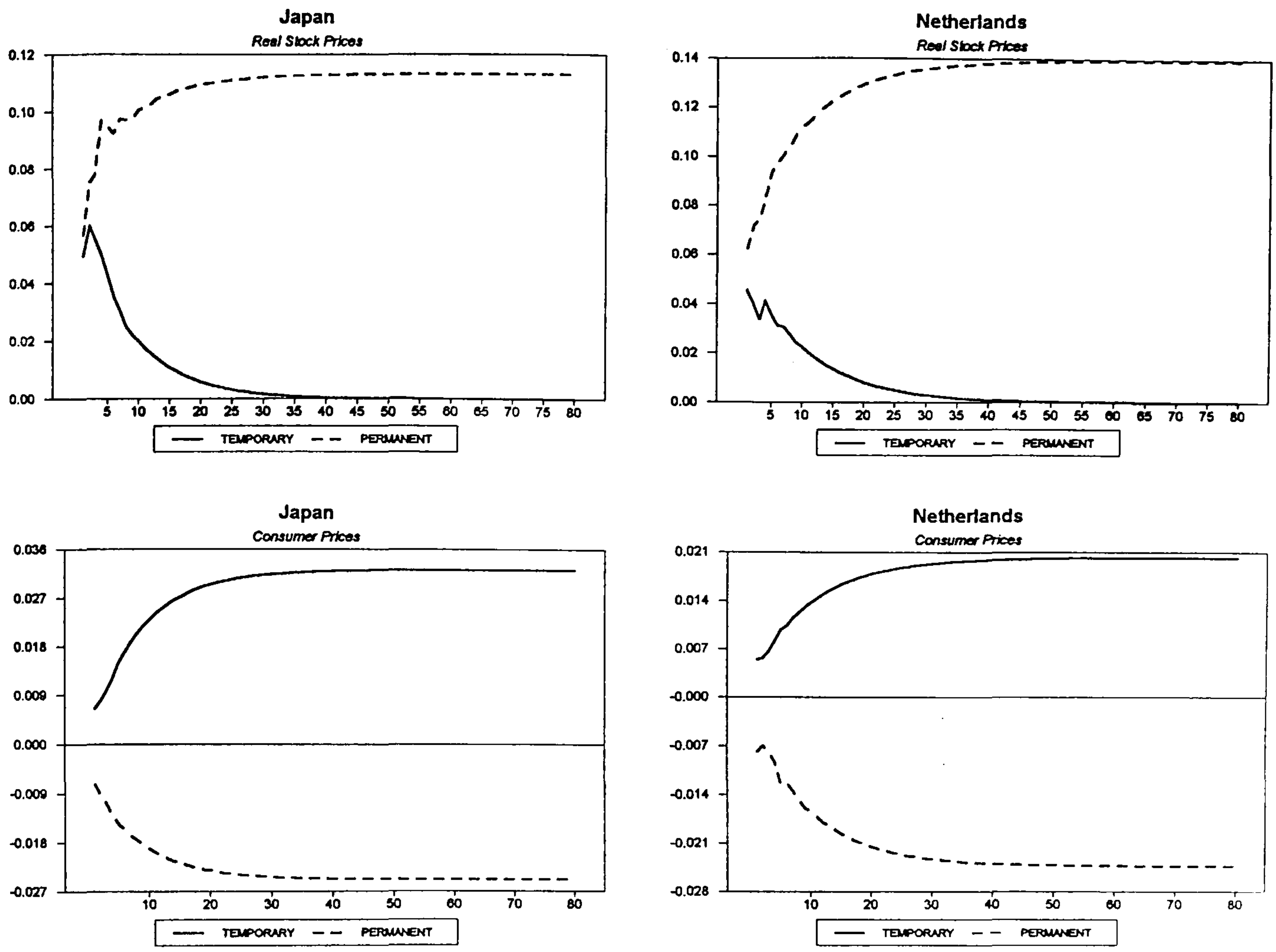


Figure 5.21: Cumulative Impulse Response Functions

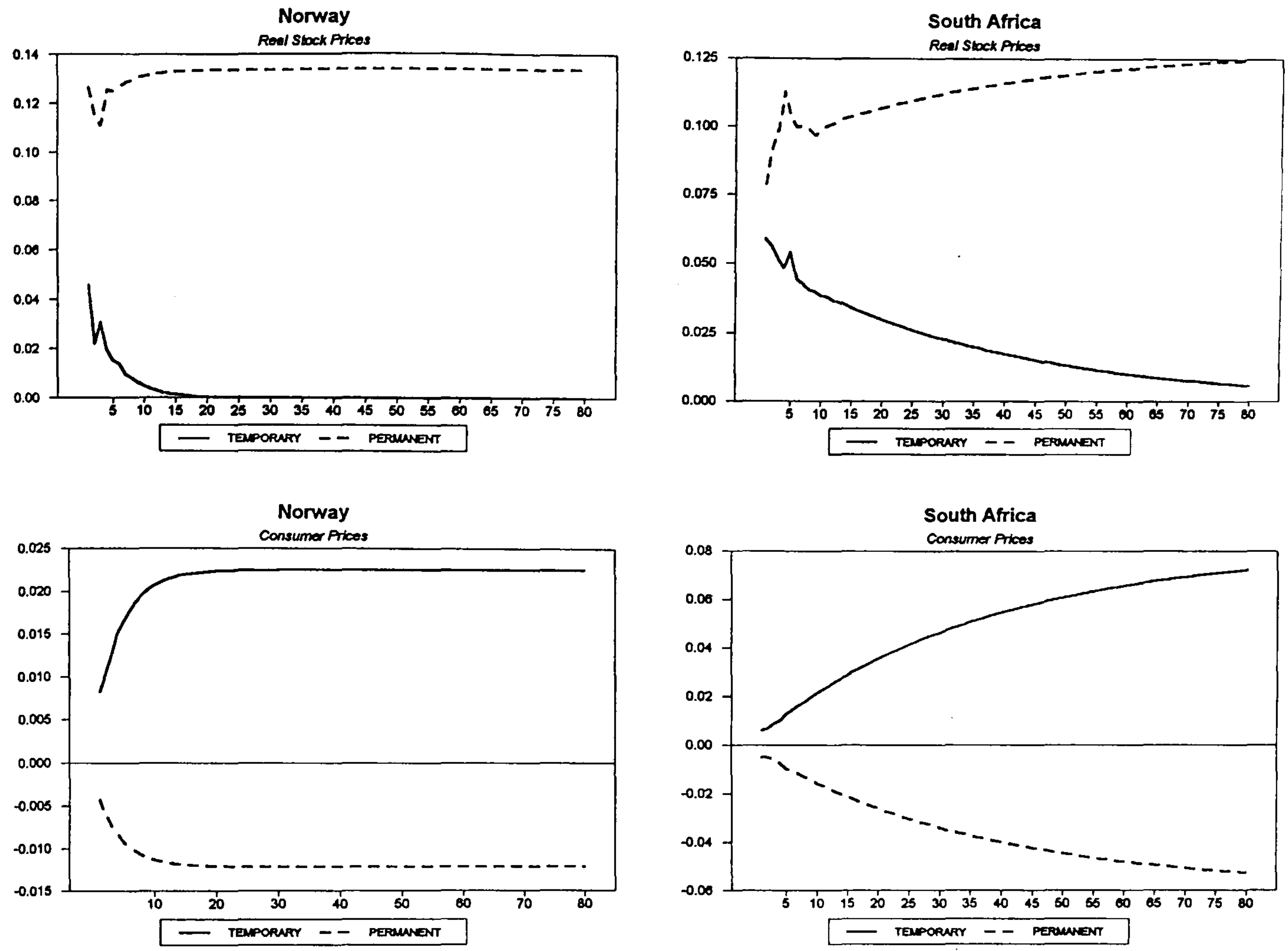


Figure 6.2g: Cumulative Impulse Response Functions

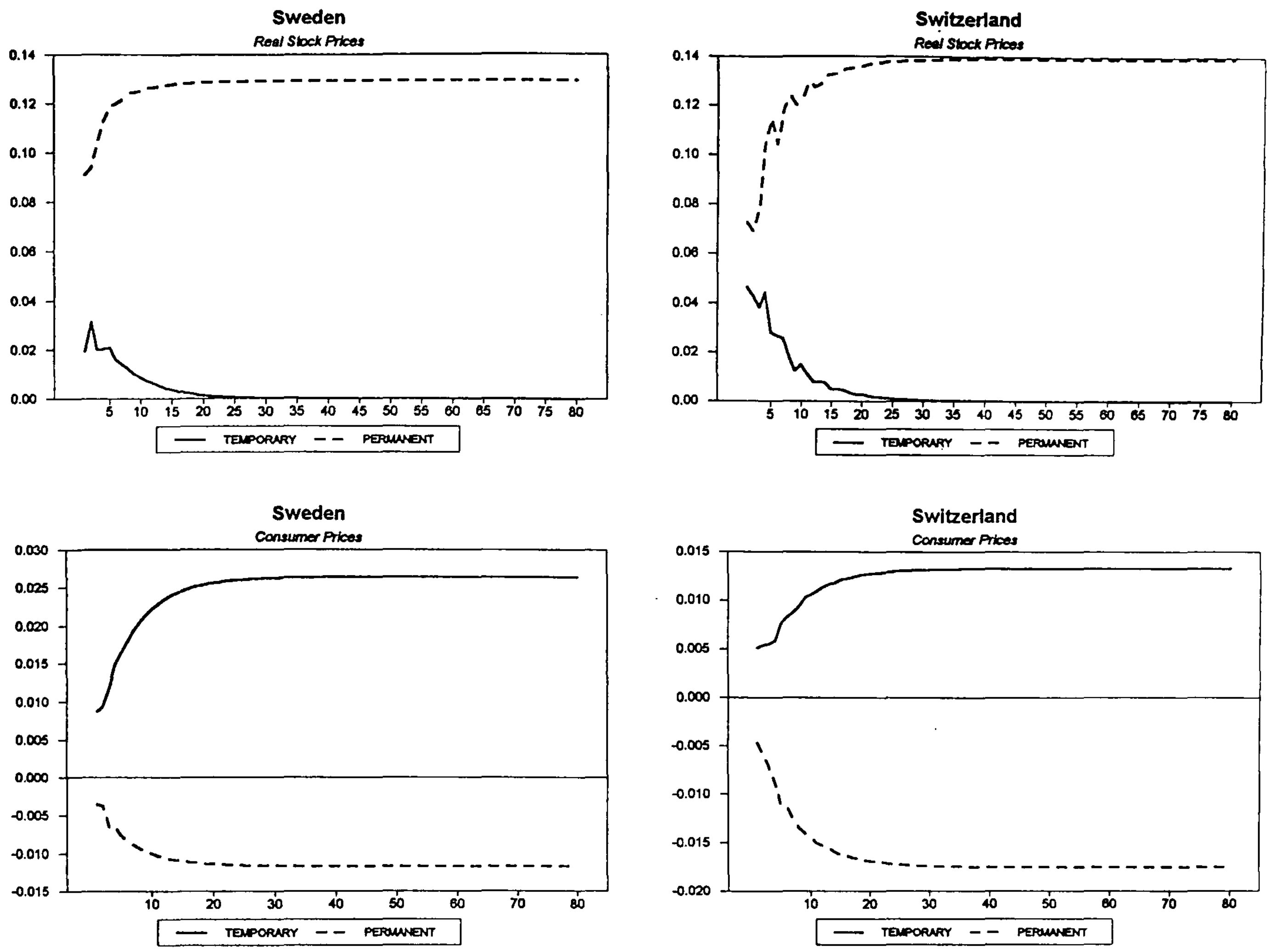
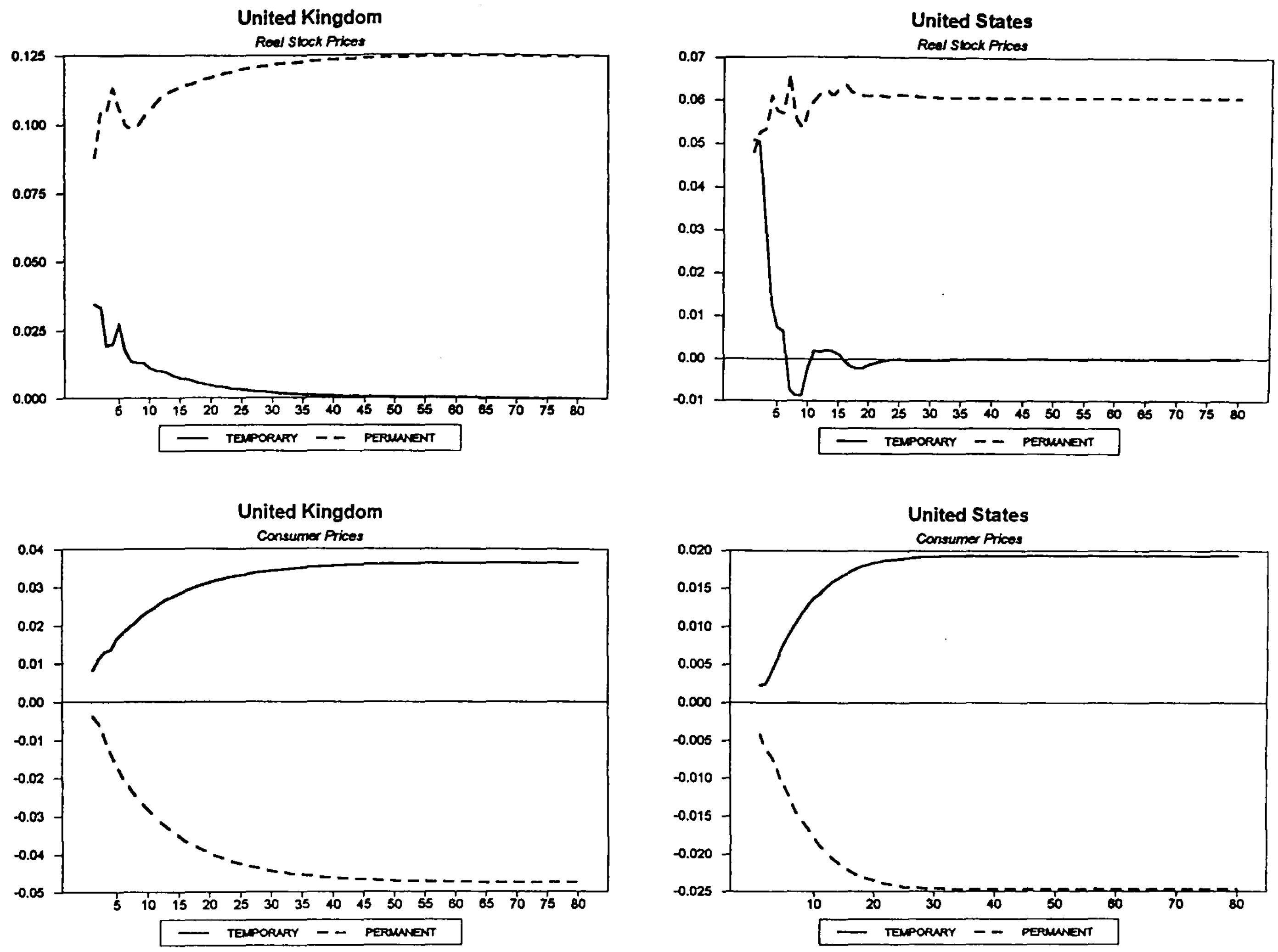


Figure 6.2h: Cumulative Impulse Response Functions



6.4 Forecast Error Variance Decomposition

Table 6.5 reports the fraction of the unconditional variation in real stock price movements (and in panel b, consumer price movements) due to temporary (aggregate demand) innovations in real stock prices (and in panel b, consumer prices) in short and long runs. The contribution of permanent (aggregate supply) innovations (not directly reported) is given by 100 minus the contribution of temporary innovations. The forecast error variance in real stock prices due to temporary innovations varies across countries - a feature of country-specific factors, such as monetary and fiscal policy. Eight of the sixteen countries exhibit a forecast error variance in excess of 30 percent, and fourteen in excess of ten percent in the long run (12-quarter horizon). Therefore, the size of the mean-reverting component (represented by temporary shocks to real stock prices) is large for the majority of countries. The size of the mean-reverting (temporary) components in real stock prices are consistent with other recent studies (for example, Cochrane and Sbordone, 1988; Fama and French, 1988; Poterba and Summers, 1988; Frennberg and Hansson, 1993; Cochrane, 1994; Cochran and DeFina, 1995; Lee, 1995). As discussed above, since the mean-reverting (temporary) component in real stock prices is attributed to aggregate demand shocks, then the size of this component is expected to be less than the mean-reverting component reported in other studies. For example, Cochrane (1994) and Lee (1995) report a mean-reverting component in excess of 50 percent.[44] Thus, the results presented support the findings of many previous studies. Moreover, since the temporary and permanent shocks are orthogonal, we can test the significance of temporary shocks to real stock prices.

We employ equation (5.1) to evaluate the proportion of real stock price movements explained by each component and the significance of each component in explaining that proportion of real stock price movements. As before, the t-statistics obtained from regressing each of these components in turn on the change in real stock prices, $(1-L)q_t$, provides a test of the statistical significance of each component. For example, regressing $(1-L)q_t$ onto $q_{T,t}$ provides a test of the statistical significance of the temporary component, where $q_{T,t}$ is the temporary disturbance to real stock prices. The R^2s associated with each least squares regression estimate the proportion of total variation in real stock returns explained by each component.

Table 6.6 reports that for all countries the temporary (or mean-reverting component) component in real stock prices is in fact statistically significant at standard significance levels, explaining between 7 and 56 percent of the variation

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[44]Earlier studies that employ long-horizon techniques, for example, Fama and French (1988a) and Poterba and Summers (1988), report a similar sized mean-reverting component. However, recent studies have criticised these findings as exhibiting low power and dependent on the inclusion of the pre-world war II period (see Richardson and Stock, 1989; Kim *et al.*, 1991; Mankiw *et al.*, 1991; Richardson, 1993; Mills, 1995). In fact, the variance ratio estimates of Kim *et al.* (1991) and Mills (1995) suggest that stock prices are mean averting for the post-war period.

in real stock prices. The results show that real stock prices exhibit a (macroeconomic aggregate demand) component that is mean-reverting and explains a significant proportion of stock price movements. Thus the results strongly support the mean reversion hypothesis.

Table 6.5: Forecast Error Variance Decomposition Due to Temporary Shocks

(a) Real Stock Prices

	Horizon		
	1-quarter	4-quarters	12-quarters
Austria	27.90	28.16	31.18
Belgium	30.28	30.39	30.48
Canada	62.36	63.10	63.98
Finland	32.56	30.36	31.51
France	9.16	10.92	11.16
Germany	10.18	11.44	12.53
India	9.19	9.72	11.70
Italy	5.85	7.35	7.49
Japan	43.29	40.03	41.34
Netherlands	34.67	34.99	34.86
Norway	11.47	14.72	14.93
S. Africa	35.90	34.71	35.24
Sweden	4.33	7.18	7.55
Switzerland	29.02	26.84	28.11
UK	13.27	14.67	15.94
US(57i-95iv)	52.82	57.97	57.79
US(25iv-95iv)	7.59	8.40	8.71
US(25iv-56iv)	1.80	2.43	2.44

(b) Consumer Prices

	Horizon		
	1-quarter	4-quarters	12-quarters
Austria	62.94	65.39	64.66
Belgium	51.95	52.98	52.06
Canada	21.65	23.86	36.54
Finland	61.68	54.36	59.75
France	88.91	86.72	89.80
Germany	72.32	66.77	63.49
India	81.09	85.92	84.68
Italy	87.84	85.98	89.38
Japan	45.96	46.15	52.64
Netherlands	33.61	34.62	33.90
Norway	78.88	77.92	77.86
S. Africa	62.45	62.86	63.58
Sweden	86.12	82.03	81.82
Switzerland	55.32	48.98	47.52
U.K.	82.95	61.11	52.28
US(57i-95iv)	23.87	31.27	36.05
US(25iv-95iv)	88.54	91.58	92.53
US(25iv-56iv)	98.68	98.04	98.04

Notes: Estimation is by ordinary least squares. The sample period is 1957i - 1995iv.

Table 6.6: Size and Significance of Permanent, Temporary and Deterministic Components in Stock Prices

Estimated Regression: $\Delta q_t = \alpha q_{i,t} + \varepsilon_t$, $I = P, T, D$

	Size (R^2)			Significance(t-Statistic)		
	Temporary	Permanent	Deterministic	Temporary	Permanent	Deterministic
Austria	0.31	0.67	0.02	8.19	17.31	1.71
Belgium	0.27	0.59	0.14	7.29	14.49	4.99
Canada	0.62	0.34	0.04	15.60	8.69	2.40
Finland	0.30	0.63	0.07	8.17	15.83	3.38
France	0.09	0.84	0.07	3.75	26.87	3.50
Germany	0.13	0.81	0.06	4.68	25.23	3.26
India	0.11	0.84	0.05	4.32	28.01	2.61
Italy	0.07	0.86	0.07	3.44	30.54	3.32
Japan	0.37	0.56	0.07	9.44	13.74	3.77
Netherlands	0.34	0.58	0.08	8.71	14.28	3.57
Norway	0.14	0.78	0.08	5.03	22.98	3.78
S. Africa	0.35	0.62	0.03	8.95	15.77	2.06
Sweden	0.07	0.88	0.05	3.55	32.32	2.91
Switzerland	0.27	0.69	0.04	7.47	18.07	2.66
UK	0.15	0.79	0.06	5.19	23.56	3.21
US(57i-95iv)	0.56	0.41	0.03	13.81	10.12	2.20
US(25iv-95iv)	0.08	0.91	0.01	4.89	53.65	1.25
US(25iv-56iv)	0.02	0.97	0.01	1.73	59.69	1.03

Notes: In the estimated regression, $\Delta q_t = \alpha q_{i,t} + \varepsilon_t$, $q_{T,t}$ is the temporary component of real stock price movements, $q_{P,t}$ is the permanent component, and $q_{D,t}$ is the deterministic component. Estimation is by ordinary least squares. The size of the components is given by the R^2 from the estimated regressions and represents the proportion of total variation in real stock returns explained by each component. The significance of the component is given by the t-statistic of the coefficient α in estimated regression. Estimation is by ordinary least squares. The sample period is 1957i - 1995iv.

6.5 Conclusion

In this chapter, we have extended the work from the previous chapter. Employing a similar multivariate innovation decomposition technique we have investigated the components of real stock prices for sixteen countries. The evidence supports the earlier findings (Chapter 5) that real stock prices contain a statistically significant mean-reverting component, explaining between 7 and 64 percent of the variation in real returns and thus that real returns are to some extent predictable (see, for example, Fama and French, 1988b; Campbell, 1990, 1991; Cochran *et al.*, 1993; Cochrane, 1994). The impulse response functions of a temporary shock on real stock prices show, however, that for some countries the mean-reverting component can be quite persistent, with estimated half lives varying between 1 and up to 25 quarters.

The multi-country analysis emphasises that the dynamic response of stock prices to temporary and permanent shocks varies across markets.[45] A number of common features include: real stock prices rise in response to a permanent shock to stock prices and continue to rise for a number of years after the shock; the mean-reverting component is statistically significant at standard significance levels.

The results are consistent with those of previous researchers who have used vector autoregressive techniques to decompose stock prices into their temporary and permanent components (Cochrane, 1994; Lee, 1995). The

[45]The different dynamic response of real stock prices suggests that there exists potential gains from international diversification.

response of consumer prices to temporary and permanent shocks is as predicted by the standard macroeconomic aggregate demand - aggregate supply model with a vertical long-run aggregate supply curve.

The issue of whether mean reversion reflects market inefficiency is debatable and - linked to the joint hypothesis problem - is unlikely to be easily resolved. For related discussion of this issue see De Long *et al.* (1990) who show that mean reversion is consistent with noise trader risk and Fama and French (1988a) who argue that mean reversion may also result form the workings of efficient markets.

Chapter 7

THE DYNAMIC RELATIONSHIP BETWEEN INTEREST RATES AND REAL STOCK PRICES

7.1 Introduction

There is a strong association between stock prices and interest rates, in theory explained by a simple rational expectations present value, and this relationship is empirically assessed by a number of studies (for example, Campbell, 1987, 1990, 1991; Fama and French, 1989; Breen, Glosten and Jagannathan, 1989; Fraser, 1995; Pesaran and Timmermann, 1995; Campbell *et al.*, 1997). In this section we investigate the interaction between stock price and interest rate movements in assessing the size and significance of the mean-reverting component in UK and US real stock prices. More specifically, we specify a multivariate time series technique based on the vector autoregressive representation, outlined in Chapter 4, section 4.1, of real stock returns and nominal interest rates to identify temporary and permanent innovations in stock price movements.

A plausible argument is that an increase in interest rates would make fixed income assets (we use the 3-month Treasury Bills as an indicator) more attractive investments, and so stock prices would have to fall to induce people to hold stocks. However, if the increase in interest rates primarily reflects revised inflationary expectations, then these changes should have little effect on stock prices (Shiller and Beltratti, 1992).[46] In the context of our estimated VAR, we use the present value relationship to identify the temporary and permanent shocks to stock prices. The temporary shock to real stock prices will cause stock prices to rise initially and then to reduce so that it has a zero long-run effect, whereas, a permanent shock increases the real stock price in the short and long run. We also expect a permanent shock to decrease interest rates, while a temporary shock will increase interest rates.

Given the evidence that innovations to financial asset returns exhibit non-normal distribution properties[47] we investigate the sensitivity of the size, significance and persistence of the mean-reverting component to two robust estimation procedures, notably the least absolute deviation (LAD) and the residual augmented least squares (RALS), in order to allow for possible non-normality of the innovations to stock returns and interest rates. The two robust estimation procedures are outlined in Chapter 4, section 4.2.

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[46]That is, there is little change in expected real dividends and therefore, by the present value model, little change in real stock prices.

[47]There is large volume of evidence that stock prices and interest rates have fat-tailed and, perhaps, skewed distributions (Badrinath and Chatterjee, 1988; Von Furstenberg and Jeon, 1989; Jansen and DeVries, 1991).

7.2 Data Sources and Properties

Monthly data were obtained from the International Monetary Fund's International Financial Statistics data base and the stock price index from Datastream for the UK and from CRSP for the US. The sample period is 1957:1 to 1995:11 for the US and 1965:1 to 1995:6 for the UK. The shorter period of analysis is chosen in order to avoid the unusual stock price behaviour in the pre-war period and the fact that the behaviour of interest rates[48] have changed over time. For the UK, we use the widely reported FTA All Share price index, available from 1965.[49] The IMF stock price index, for the 1957:1-1995:6 was also considered and generated very similar findings (these are not reported to conserve space).

The data series of interest are the natural logarithm of the real stock price index[50], q_t, and the monthly rate of return on 3-month Treasury bills, r_t. The real stock price index is constructed using the respective consumer price index. The monthly rate of return on 3-month Treasury bills is calculated geometrically by

$$(5.2) \qquad r_t = \left(r_t^* + 1\right)^{(1/12)} - 1$$

---

[48]For the US, the period preceding the Federal Reserve Board-Treasury Accord in 1951 the Federal Reserve Board held interest rates relatively constant.

[49]The UK stock price index, from the IMF's IFS data base, for the 1957:1-1995:6 was also considered and generated very similar findings (these are not reported to conserve space).

[50]The US stock price index is the S&P500 stock price index and the UK stock price index is the FTA All Share price index. The consumer price index for the US is obtained from the SBBI files and for the UK is obtained from the IFS data base.

where r_t^* is the annualized rate of return on 3-month t-bills in period t.[51] The logarithm of the real stock price and the interest rates series (and their first differences) are presented in Figures 7.1 and 7.2.

Table 7.1 reports summary statistics on the series of interest - both the US and UK real stock prices and interest rates series reveal persistence and suggest that the series are nonstationary. The unit root tests, reported in Table 7.2, confirm this. The augmented Dickey-Fuller (ADF) and Phillips-Perron Z_t (PP) tests support the null hypothesis that real stock price and interest rates are first-difference stationary.[52]

The results from the RALSDF test, reported in Table 7.2, indicate a substantial gain in efficiency in employing the RALS adjusted DF rather than the standard DF test. For the US, the efficiency gain statistic $\hat{\eta}$ is 0.89 and 0.64 for real stock prices and interest rates, respectively. Real stock prices are strongly I(1) whereas interest rates are I(1) at the one percent significance level. Similarly, for the UK, $\hat{\eta}$ is 0.78 and 0.77 for real stock prices and interest rates, respectively, and real stock prices and interest rates are strongly I(1) processes. From this evidence we conclude that, for both countries, real stock prices and interest rates

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[51]Calculating r_t arithmetically, i.e. r_t^* /12, does not significantly change the results.

[52]This finding is not sensitive to the choice of lag depth in the auxiliary ADF regressions or in calculating the PP tests.

are I(1).[53]

As a test for cointegration, the results of the ADF test for a unit root in the least squares residual from a regression of r_t onto q_t and a constant are reported in Table 7.2 (final column). The null hypothesis of no cointegration cannot be rejected at the 5% level of significance.

[53]The residuals in the RALSDF for the US interest rates series is serially correlated and for this reason it is more appropriate to use either the ADF or PP that includes sufficient lags to ensure whiteness of residuals.

Table 7.1: Summary Statistics

(a) United States

	p_t	Δp_t	r_t	Δr_t
Mean	-	0.19	0.48	0.00
σ	-	4.19	0.22	0.04
ρ(k)	Autocorrelation			
k = 1	0.98*	0.06	0.98*	0.29*
2	0.96*	-0.01	0.95*	-0.10
3	0.94*	0.02	0.93*	-0.10
4	0.93*	0.02	0.91*	-0.04
5	0.91*	0.10	0.89*	0.04
6	0.89*	-0.05	0.87*	-0.19*
7	0.87*	-0.05	0.85*	-0.19*
8	0.85*	-0.05	0.84*	0.08
9	0.84*	-0.01	0.83*	0.19
10	0.82*	0.01	0.81*	0.06
11	0.80*	-0.01	0.79*	0.00
12	0.79*	0.02	0.77*	-0.09

(b) United Kingdom

	q_t	Δq_t	r_t	Δr_t
Mean	-	0.14	0.73	0.00
σ	-	6.08	0.23	0.07
ρ(k)	Autocorrelation			
k = 1	0.98*	0.12*	0.98*	0.22*
2	0.96*	-0.09	0.94*	0.06
3	0.95*	0.06	0.91*	-0.05
4	0.93*	0.05	0.87*	0.02
5	0.91*	-0.08	0.84*	0.05
6	0.89*	-0.02	0.80*	0.04
7	0.88*	0.03	0.76*	-0.01
8	0.86*	-0.00	0.72*	0.07
9	0.84*	0.09	0.68*	-0.06
10	0.82*	0.02	0.65*	-0.03
11	0.80*	-0.04	0.62*	0.03
12	0.78*	0.00	0.58*	-0.01

Notes: The mean and standard deviation, σ, are expressed in percentage terms. ρ(k) = autocorrelation between x_t and x_{t-k}. r_t is the monthly rate of return on 3-month Treasury bills, estimated from equation (5.2); q_t is the natural logarithm of real stock prices. Δ=(1-L) denotes the first difference. An asterisk denotes the sample autocorrelation is at least two standard deviations to the left or to the right of its expected value under the hypothesis that the true autocorrelation is zero. The sample period is 1957:1-1995:11 for the US and 1965:1-1995:6 for the UK.

Table 7.2: Unit Root and Cointegration Tests:
Interest Rates and Real Stock Prices

(a) United States

	$\Delta^2 r_t$	Δr_t	r_t	$\Delta^2 q_t$	Δq_t	q_t	μ_t
ADF	-15.60	-10.36	-1.92	-12.63	-7.97	-1.24	-2.33
PP	-36.41	-15.57	-2.32	-55.23	-20.37	-1.20	
RALSDF	-40.80	-21.55	-3.30	-38.76	-20.29	0.15	
	(0.53)	(0.64)	(0.64)	(0.87)	(0.90)	(0.89)	

(b) United Kingdom

	$\Delta^2 r_t$	Δr_t	r_t	$\Delta^2 q_t$	Δq_t	q_t	μ_t
ADF	-19.93	-11.74	-2.55	-24.40	-14.02	-1.50	-2.67
PP	-29.21	-15.13	-2.21	-29.39	-16.90	-1.38	
RALSDF	-28.79	-14.03	-1.96	-33.70	-18.70	-0.14	
	(0.78)	(0.78)	(0.77)	(0.77)	(0.78)	(0.78)	

Notes: r_t is the monthly rate of return on 3-month Treasury bills; q is the natural logarithm of real stock prices. μ is the ordinary least squares regression of r_t onto q_t and a constant. The unit root tests are the Augmented Dickey-Fuller test statistic (ADF) and the Phillips-Perron Z_t test statistic (PP), without time trend and with constant, for the null hypothesis that the series is I(1) (see, Perron, 1988); the lag truncation was set at one. For a 5% significance level the critical ADF and Z_t is -2.88. RALSDF is the residual augmented least square Dickey-Fuller unit root test. The figures in parenthesis is the efficiency gain statistic, $\hat{\eta}$, in using the RALSDF than the standard DF statistic. The cointegration test, μ_t, is the augmented Dickey-Fuller test; for a 5% significance level the critical value is -3.17 (see, Fuller, 1976, pp. 371-3; and Engle and Granger, 1987). The sample period is 1957:1-1995:11 for the US and 1965:1-1995:6 for the UK.

Figure 7.1: Interest Rates and Real Stock Prices

United States, 1957:1-1995:11

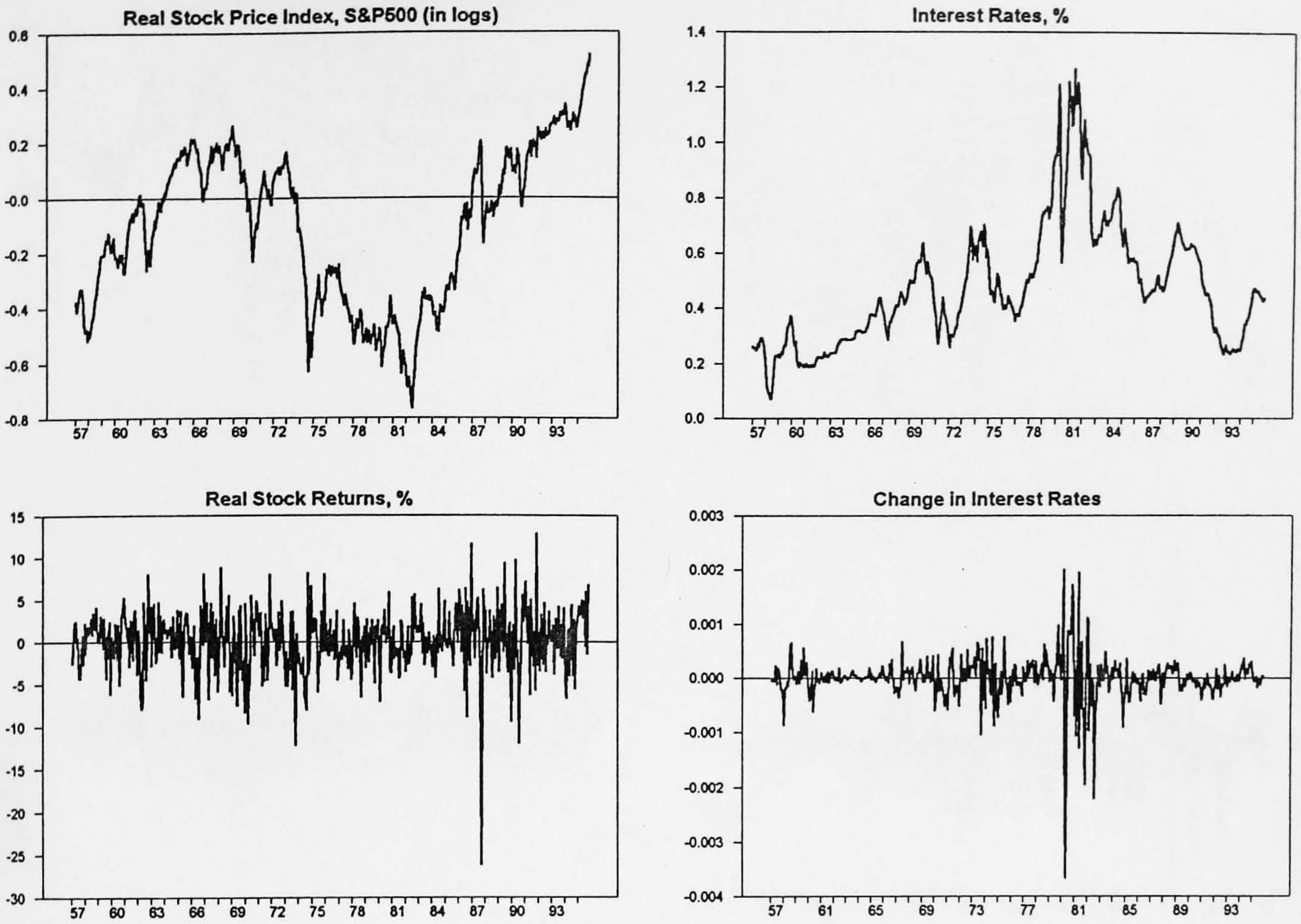
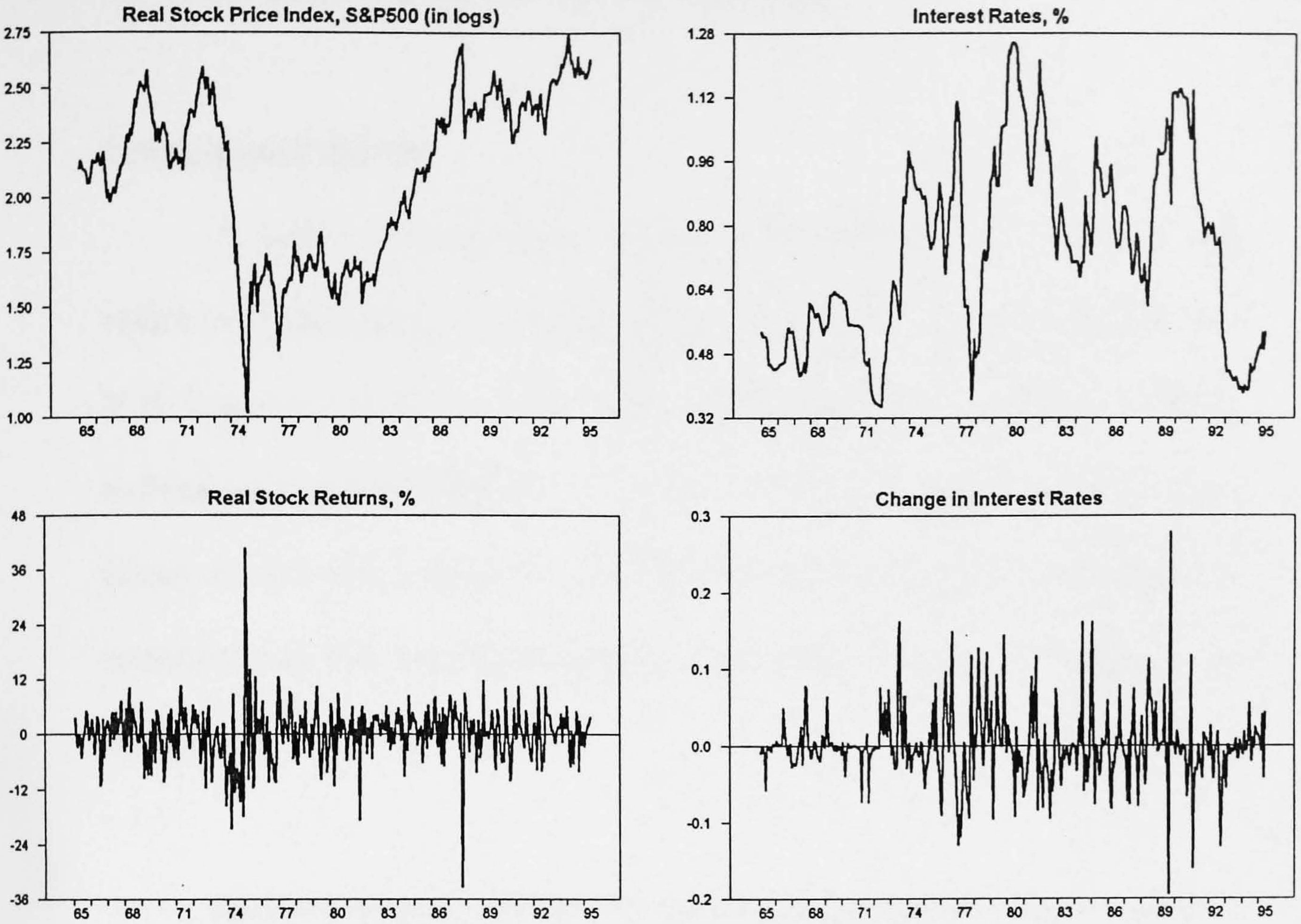


Figure 7.2: Interest Rates and Real Stock Prices

United Kingdom, 1965:1-1995:6



7.3 Decomposing US Stock Price Movements

Least Squares Results

A vector autoregressive representation of $[(1\text{-}L)q_t \quad (1\text{-}L)r]'$ was estimated[54] preliminary to effecting the decomposition. The lag length for the VAR was chosen as follows. First, using the Bayes Information Criterion (BIC), an initial lag length was determined.[55] Second, using the Ljung-Box Q-statistic we tested for the whiteness of the residuals and the lag depth was increased (if necessary) until they were approximately white noise. The chosen lag depth was fourteen.

Given the estimates of the VAR parameters (reported in Table 7.3) and the covariance matrix of VAR residuals (Table 7.4), we then carried out the VAR decomposition, as outlined in Chapter 4, section 4.1. Using the estimated A(0) matrix (reported in Table 7.5) we generated the impulse response functions for stock prices. The cumulative impulse response functions are reported in Figure 7.3. A one unit (standard deviation) temporary shock to real stock prices has a half-life of seven months. A permanent shock to real stock prices increases stock prices for the first eight months, then stock prices reduce (reversal in stock price movement) up to the 20th month to a stabilizing level that is slightly higher than the initial effect. A permanent shock to interest rates decreases interest rates,

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[54]Seasonal dummies were included in the VAR.

[55]The BIC chose a lag length of one and AIC chose six.

whereas a temporary shock increases interest rates.

Along with the natural logarithm of real stock prices, the innovations to real stock prices are cumulated and presented in Figure 7.4. Similar to Figure 5.8, Figure 7.4 illustrates the different components of (the natural logarithm of) real stock prices; the deterministic components are the trend and seasonal elements, the temporary component plot line adds the cumulated temporary innovations to the deterministic component, and the permanent component plot line then adds the cumulated permanent innovations to the temporary component plot line. Thus, the difference between the deterministic and temporary components measures the temporary innovations in real stock prices over the period. The difference between the termporary and permanent components measure the permanent innovations in real stock prices.

The temporary component reported in Figure 7.4 indicates that the temporary innovations are stationary around the deterministic component, but take long swings away from the deterministic trend - evidence of a slowly decaying stationary component, i.e, stock prices take long temporary swings away from fundamental values (Summers, 1986; Fama and French, 1988a, De Long *et al.*, 1990). The size of the temporary innovations are small relative to the permanent innovations, however, as we see below they still explain a significant (and substantial) proportion of the variance in real stock prices.

In fact, as reported in Table 7.6, at the one-month horizon 24 percent of the forecast error variance in real stock prices is due to temporary innovations, increasing slightly to 25 percent in the long run. The size of this mean-reverting component in real stock prices is lower than reported in other recent studies (for example, Fama and French, 1988; Cochrane, 1994; Lee, 1995). As discussed above, one would expect the temporary component estimated by Cochrane (1994) and Lee (1995) to be larger in magnitude because the permanent component is not necessarily a pure random walk and thus contains a mean-reverting element. Thus, the results presented in this paper are not inconsistent with those of previous studies.

Since the shocks are orthogonal and, as in equation (5.1), must sum to $x_t = [(1\text{-}L)q_t \ \ (1\text{-}L)r_t\,]'$. The t-statistics obtained from regressing each of these components in turn on the change in real stock prices, $(1\text{-}L)q_t$, provides a test of the statistical significance of each component.[56] The R^2s associated with each least squares regression estimate the proportion of total variation in real stock returns explained by each component.[57] Table 7.7 reports that the mean-reverting (temporary) component is in fact statistically significant at standard significance

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[56]Therefore, regressing $(1\text{-}L)q_t$ onto $q_{T,t}$ provides a test of the statistical significance of the temporary component.

[57]The above findings are conditional on the orthogonality of the shocks to stock prices. This can easily be tested by regressing one shock on the other shock:

$$\begin{array}{lll} q_{T,t} = & 0.0019\, q_{P,t} & R^2 = 0.0000 \\ & (0.0274) & SSE = 0.1606 \\ & [0.0709] & DW = 2.1669 \end{array}$$

The R^2 of zero indicates that the temporary shock to real stock prices is uncorrelated with the permanent shock to real stock prices.

levels for real stock prices, explaining 25 percent of the variation. 72 percent of the variation in real stock prices is explained by permanent innovations while 3 percent is explained by trend and seasonal components.

Table 7.3: VAR Parameter Estimates: OLS, LAD and RALS

		OLS	LAD	RALS
(1-L) q_t	(1-L) q_{t-1}	0.02308	-0.02785	0.0304
		(0.05000)	(0.03430)	(0.0477)
	(1-L) q_{t-2}	-0.01734	0.00307	0.0082
		(0.04993)	(0.03402)	(0.0467)
	(1-L) q_{t-3}	0.00782	0.00838	0.0499
		(0.05000)	(0.03413)	(0.0466)
	(1-L) q_{t-4}	-0.03382	0.04712	0.0483
		(0.05000)	(0.03442)	(0.0467)
	(1-L) q_{t-5}	0.10202*	0.11849*	0.1237*
		(0.04990)	(0.03420)	(0.0466)
	(1-L) q_{t-6}	-0.03634	0.01082	-0.0365
		(0.05016)	(0.03421)	(0.0467)
	(1-L) q_{t-7}	0.01461	-0.07923*	-0.0135
		(0.05025)	(0.03432)	(0.0468)
	(1-L) q_{t-8}	-0.09775*	-0.05099	-0.0338
		(0.05015)	(0.03429)	(0.0467)
	(1-L) q_{t-9}	0.03721	0.04234	0.0565
		(0.05043)	(0.03452)	(0.0468)
	(1-L) q_{t-10}	-0.02741	-0.08942*	-0.0457
		(0.05022)	(0.03420)	(0.0464)
	(1-L) q_{t-11}	0.04029	-0.02797	0.0317
		(0.05009)	(0.03401)	(0.0465)
	(1-L) q_{t-12}	-0.05324	0.01039	0.0276
		(0.05002)	(0.03387)	(0.0461)
	(1-L) q_{t-13}	0.03114	0.03369	-0.0419
		(0.05014)	(0.03382)	(0.0463)
	(1-L) q_{t-14}	-0.05081	-0.01478	-0.0383
		(0.05011)	(0.03504)	(0.0463)
	(1-L) r_{t-1}	-10.78792*	-18.20320*	-14.8889*
		(5.12545)	(3.31994)	(5.2758)
	(1-L) r_{t-2}	4.04944	9.85203*	4.7043
		(5.41819)	(3.37026)	(5.5822)
	(1-L) r_{t-3}	-7.32121	-18.8545*	-9.1671
		(5.44074)	(3.37786)	(5.5807)
	(1-L) r_{t-4}	-4.12724	2.05356	-1.5425
		(5.40851)	(3.36966)	(5.5462)
	(1-L) r_{t-5}	-7.16911	-10.94846*	-9.0359
		(5.41957)	(3.39443)	(5.5508)
	(1-L) r_{t-6}	-0.20305	4.53544	1.3439
		(5.43585)	(3.32924)	(5.5696)
	(1-L) r_{t-7}	-5.16702	-10.06469	-7.8729
		(5.56870)	(3.42942)	(5.7044)
	(1-L) r_{t-8}	0.28296	8.53932*	6.2590
		(5.57523)	(3.40585)	(5.7164)
	(1-L) r_{t-9}	0.72665	-4.17404	-2.1051
		(5.39516)	(3.38309)	(5.5304)
	(1-L) r_{t-10}	-8.47124	-12.7173*	-7.7119
		(5.39884)	(3.39395)	(5.5537)
	(1-L) r_{t-11}	-1.10946	-7.09256*	0.3012
		(5.40521)	(3.40124)	(5.5637)
	(1-L) r_{t-12}	-1.59620	6.44241	1.4100
		(5.43257)	(3.34710)	(5.5712)
	(1-L) r_{t-13}	-6.98644	-16.9693*	-13.8326*
		(5.37998)	(3.39844)	(5.4988)
	(1-L) r_{t-14}	5.94469	18.3713*	8.6543
		(5.12096)	(3.90394)	(5.2523)
Statistics:				
Number of Usable Obs.		452	452	452
R^2		0.09	0.06	0.39
Sum of Squared Errors		0.60	0.74	0.47
Ljung-Box Q(36)		15.02 [0.99]		17.18 [0.99]
Jarque-Bera				154.24
Skewness				-0.82
Kurtosis				3.46
Efficiency ($\hat{\eta}$)				0.88

(1-L) r_t	(1-L) q_{t-1}	0.0004936	0.0008332*	0.00081*
		(0.0004817)	(0.0002503)	(0.0464)
	(1-L) q_{t-2}	0.0005587	0.0002773	0.00066*
		(0.0004815)	(0.0002482)	(0.0465)
	(1-L) q_{t-3}	0.0005716	0.0003865	0.00081*
		(0.0004822)	(0.0002490)	(0.0464)
	(1-L) q_{t-4}	-0.0003149	-0.0002100	-0.00021
		(0.0004821)	(0.0002511)	(0.0465)
	(1-L) q_{t-5}	0.0001367	0.0001636	0.00022
		(0.0004812)	(0.0002495)	(0.0464)
	(1-L) q_{t-6}	0.0006711	0.0003772	0.00087*
		(0.0004837)	(0.0002496)	(0.0465)
	(1-L) q_{t-7}	0.0001936	0.0000517	-0.00005
		(0.0004846)	(0.0002504)	(0.0467)
	(1-L) q_{t-8}	0.0008094	0.0005461*	0.00087*
		(0.0004836)	(0.0002502)	(0.0466)
	(1-L) q_{t-9}	0.0005909	0.0003480	0.00087*
		(0.0004863)	(0.0002519)	(0.0466)
	(1-L) q_{t-10}	0.0002852	0.0001778	0.00010
		(0.0004843)	(0.0002495)	(0.0463)
	(1-L) q_{t-11}	-0.0001911	0.0000354	-0.00010
		(0.0004830)	(0.0002481)	(0.0463)
	(1-L) q_{t-12}	-0.0000269	0.0000597	-0.00015
		(0.0004823)	(0.0002471)	(0.04620
	(1-L) q_{t-13}	0.0000390	0.0001803	0.00008
		(0.0004835)	(0.0002468)	(0.0462)
	(1-L) q_{t-14}	0.0002982	0.0001627	0.00044
		(0.0004832)	(0.0002557)	(0.0460)
	(1-L) r_{t-1}	0.3577749*	0.385818*	0.2547*
		(0.0494236)	(0.024223)	(5.3301)
	(1-L) r_{t-2}	-0.1641680*	0.039754	0.0195
		(0.0522464)	(0.024590)	(5.7878)
	(1-L) r_{t-3}	0.0296377	-0.126415	-0.0214
		(0.0524638)	(0.024645)	(5.5871)
	(1-L) r_{t-4}	-0.1013245*	0.075057*	-0.0621
		(0.0521531)	(0.024585)	(5.5504)
	(1-L) r_{t-5}	0.1385411*	0.084086*	0.1033*
		(0.0522596)	(0.024766)	(5.5553)
	(1-L) r_{t-6}	-0.2547599*	-0.116194*	-0.2191*
		(0.0524167)	(0.024290)	(5.6362)
	(1-L) r_{t-7}	-0.0156037	-0.048558*	-0.0377
		(0.0536977)	(0.025021)	(5.7714)
	(1-L) r_{t-8}	0.1166039*	0.113134*	0.1598*
		(0.0537607)	(0.024849)	(5.7266)
	(1-L) r_{t-9}	0.1261307*	0.091018*	0.1688*
		(0.0520243)	(0.024683)	(5.5357)
	(1-L) r_{t-10}	-0.0671750	-0.053898*	-0.0466
		(0.0520598)	(0.024762)	(5.5476)
	(1-L) r_{t-11}	0.1282677*	0.105857*	0.0811*
		(0.0521212)	(0.024816)	(5.5585)
	(1-L) r_{t-12}	-0.1193321*	-0.012281	-0.0820*
		(0.0523850)	(0.024421)	(5.5599)
	(1-L) r_{t-13}	0.0469021	-0.017220	0.0355
		(0.0518779)	(0.024795)	(5.4941)
	(1-L) r_{t-14}	0.1460722*	0.052166	0.1638*
		(0.0493802)	(0.028483)	(5.2659)
Statistics:				
Number of Usable Obs.		452	452	452
R^2		0.27	0.18	0.57
Sum of Squared Errors		0.00	0.00	0.00
Ljung-Box Q(36)		40.96 [0.26]		51.41 [0.04]
Jarque-Bera				2296.04
Skewness				-1.16
Kurtosis				13.43
Efficiency ($\hat{\eta}$)				0.78

Notes: The figures in parenthesis denote estimated standard errors. The deterministic parameters are not reported. The Jarque-Bera is asymptotically distributed as $\chi^2(2)$ and the critical value is 5.991 at the 5% level of signicance. The skewness and Kurtosis statsitics are from Kendall and Stuart (1958) and the critical values are 0.22 and 0.45 at the 5% level of significance, respectively. An asterisk denotes statistically significant at the 5% level. The statistic $\hat{\eta}$ measures efficiency gain from employing RALS as opposed to OLS. The sample period is 1957:1-1995:11.

Table 7.4: Covariance Matrix of VAR Residuals - US

OLS	$\begin{bmatrix} 1.3173e-3 & -2.2207e-6 \\ -2.2207e-6 & 1.2249e-7 \end{bmatrix}$
LAD	$\begin{bmatrix} 1.6347e-3 & -2.9458e-6 \\ -2.9458e-6 & 1.3685e-7 \end{bmatrix}$
RALS	$\begin{bmatrix} 1.5682e-3 & -2.9880e-6 \\ -2.9880e-6 & 1.1986e-7 \end{bmatrix}$

Table 7.5: A(0) Matrix - US

OLS	$\begin{bmatrix} 0.0179 & 0.0316 \\ 2.6971e-4 & -2.2303e-4 \end{bmatrix}$
LAD	$\begin{bmatrix} 0.0263 & 0.0307 \\ 2.2832e-4 & -2.9108e-4 \end{bmatrix}$
RALS	$\begin{bmatrix} 0.0217 & 0.0331 \\ 2.4109e-4 & -2.4848e-4 \end{bmatrix}$

Table 7.6: Forecast Error Variance Decomposition

Percentage of Variance Due to Temporary Shocks:

Horizon (months)	Interest Rates	Stock Prices
1	59.39	24.28
2	60.88	24.45
3	60.41	24.45
4	59.88	24.54
5	60.01	24.90
6	59.94	24.51
12	59.45	25.15
24	59.82	25.41
36	59.87	25.43

Percentage of Variance Due to Permanent Shocks:

Horizon (months)	Interest Rates	Stock Prices
1	40.61	75.72
2	39.12	75.55
3	39.59	75.55
4	40.12	75.46
5	39.99	75.10
6	40.06	75.49
12	40.55	74.85
24	40.18	74.59
36	40.13	74.57

Notes: Estimation is by ordinary least squares. The sample period is 1957:1 - 1995:11.

Table 7.7: t-Statistic of Permanent and Temporary Components in Real Stock Prices

Decomposition by	$(1\text{-}L)q_t = \alpha q_{i,t} + \varepsilon_t$,	i=P,T,D
OLS	(a) $(1\text{-}L)q_t = 1.01q_{T,t}$	R^2=0.25
	(0.08)	SSE=0.50
	[12.18]	DW=1.78
	(b) $(1\text{-}L)q_t = 1.00q_{P,t}$	R^2=0.72
	(0.03)	SSE=0.18
	[34.41]	DW=2.06
	(c) $(1\text{-}L)q_t = 1.02q_{D,t}$	R^2=0.03
	(0.26)	SSE=0.64
	[3.88]	DW=1.92

Notes: $q_{T,t}$ is the temporary component of real stock price movements, $q_{P,t}$ is the permanent component, and $q_{D,t}$ is the deterministic component. L is the lag operator. Estimation is by ordinary least squares. Figures in parentheses denote estimated standard errors. Figures in brackets denote standard t-statistics. The sample period is 1957:1-1995:11.

Figure 7.3: Cumulative Impulse Response Functions

United States, 1957:1 - 1995:11

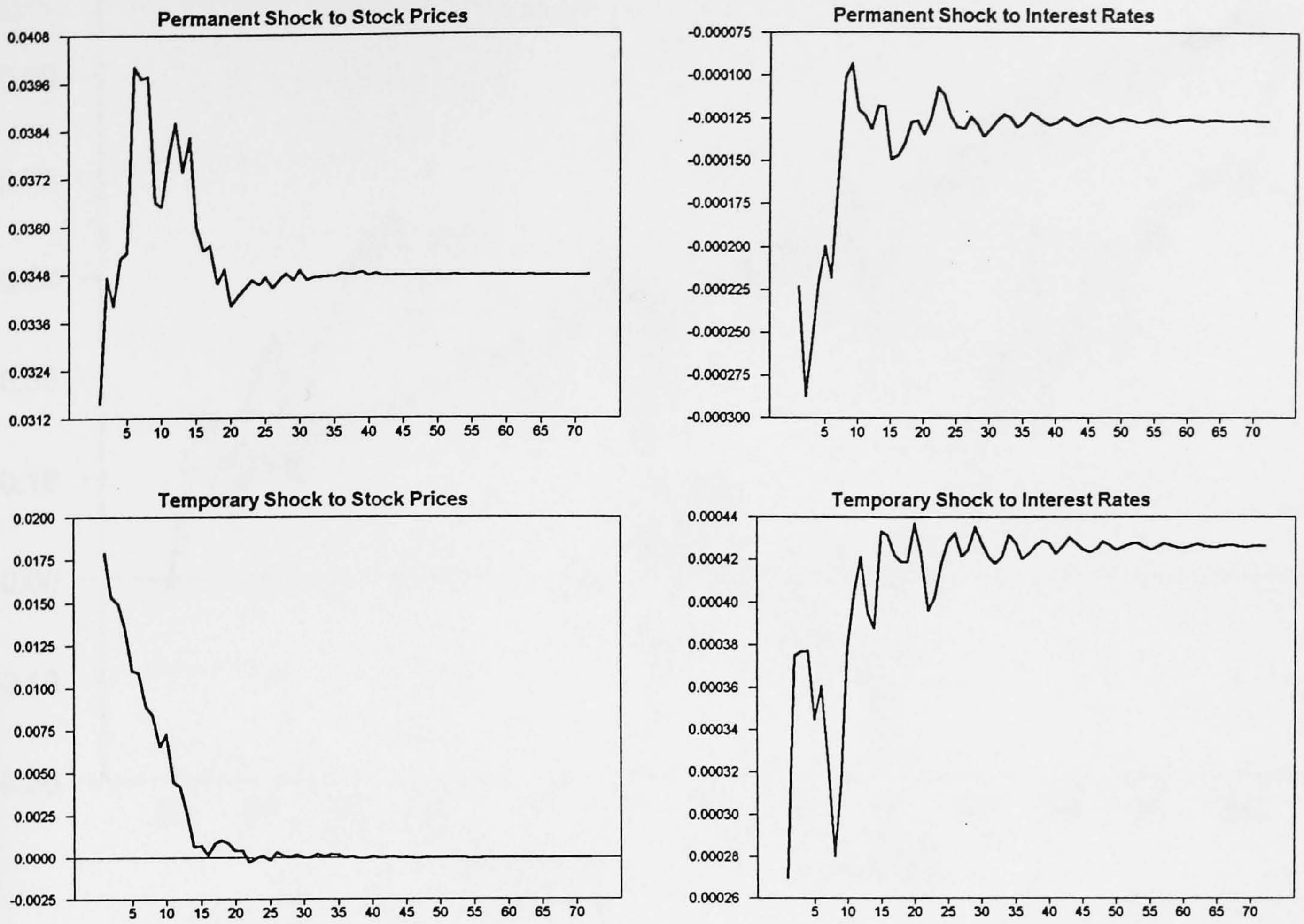
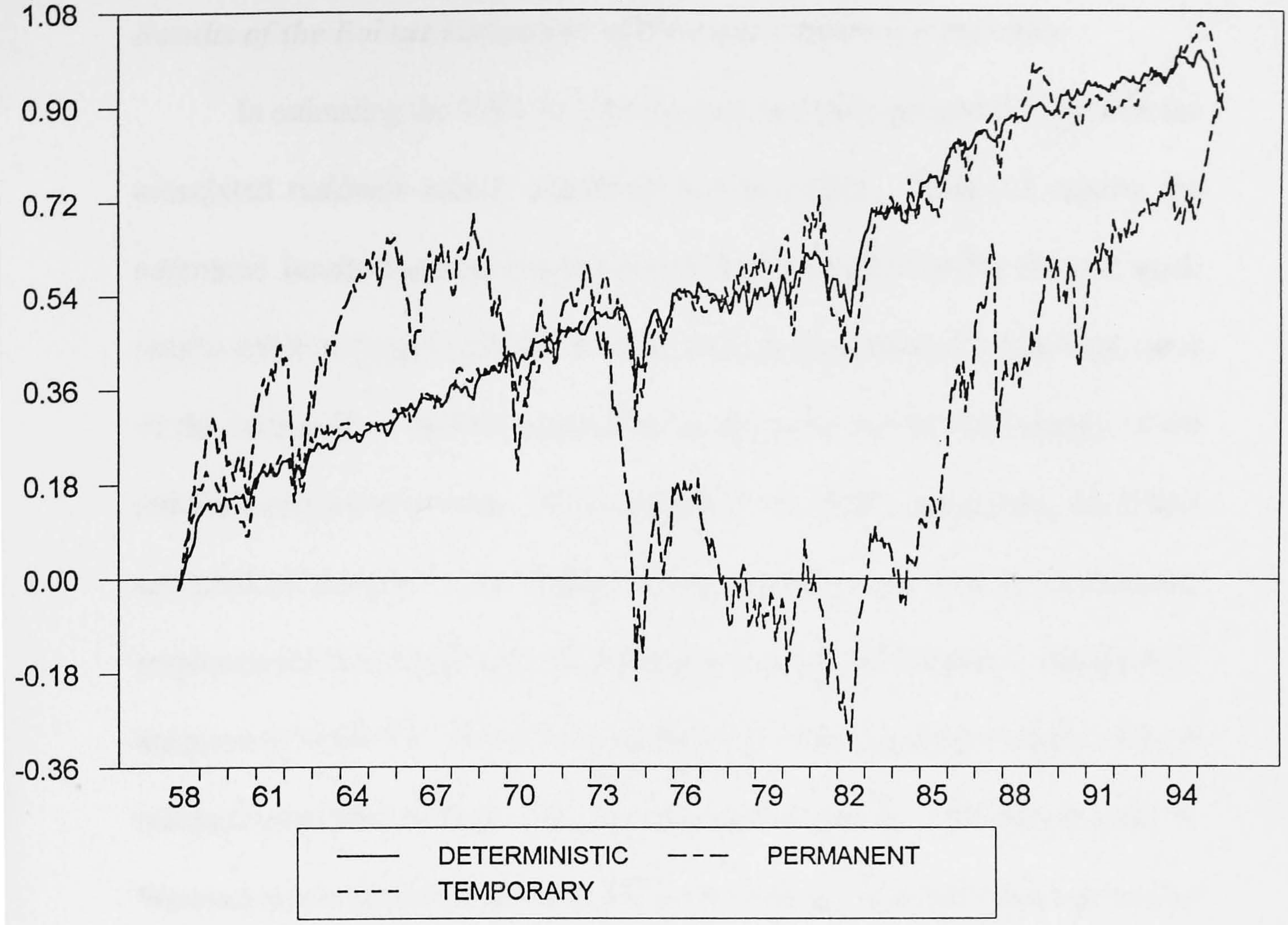


Figure 7.4: Components of Real Stock Prices

United States, 1957:1 - 1995:11



Results of the Robust Estimation of the mean-reverting component

In estimating the VAR by least squares, we have ignored the fact that the associated residuals exhibit significant non-normality. Table 7.3 reports the estimated Jarque-Bera test statistics as 154.24 and 2296.04 for the real stock returns and the change in interest rates regressions, respectively.[58] The large value of the Jarque-Bera statistic appears to be primarily due to the kurtosis of the residuals and not skewness. We re-estimated the VAR system using the RALS and LAD estimators.[59] The VAR parameter estimates and their standard errors, employing the RALS and LAD estimation procedures (see Chapter 4, section 4.2), are given in Table 7.3. Given these estimates and the covariance matrix of VAR residuals (reported in Table 7.4), we then carried out the VAR decomposition. We estimate the efficiency statistic $\hat{\eta}$ to be 0.88 and 0.78 in the VAR regressions of real stock returns and changes in interest rates, respectively, indicating efficiency gains of around twelve and twenty two percent respectively, in using the RALS over the LS estimation procedure.

As in the LS case, the RALS and LAD estimated A(0) matrices (reported in Table 7.5) are used to estimate the temporary and permanent innovations in real stock prices and are presented in Figures 7.5 and 7.6. The figures are similar to the LS case, in that the size of the temporary innovations are relatively small - this

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[58] Under the null hypothesis of Gaussian errors, the Jarque-Bera statistic is asymptotically distributed as $\chi^2(2)$ (see Cuthbertson *et al.*, 1992).

[59] Before we estimated the VAR, $(1-L)q_t$ and $(1-L)r_t$ were deseasonalised by regressing $(1-L)q_t$ (and similarly for interest rates) onto seasonal dummies and taking the residuals as the deseasonalised series.

is especially evident in the LAD case.

From the RALS and LAD estimation of the VAR decomposition, the temporary, permanent and deterministic components of the real stock return series, are calculated as before. We estimate the significance of the mean-reverting component by regressing each component in turn on the change in real stock prices using ordinary least squares.[60] The results, reported in Table 7.8, are in fact similar to those found when we used LS to estimate the decomposition and the error variance in real stock prices (see Table 7.7).

From the RALS procedure, 30 percent of the variation in real stock price movements can be explained by temporary shocks. The LAD procedure estimates that 40 percent of the variation in real stock price movements can be explained by the mean-reverting component. There are noticeable differences between the LAD and RALS cumulative impulse response functions. First, the temporary component of real stock prices is more persistent in the LAD case. Second, the amount of price reversal of stock prices to a permanent shock is not as large in the LAD case. These features provide an insight into the different sized estimated mean-reverting component.

The mean-reverting component remains highly significant. The non-normality in the least squares VAR residuals causes the size of the mean-reverting

[60]The orthogonality condition empirically holds for the shocks estimated by either the RALS or LAD.

component to be underestimated when estimated by LS. However, the earlier qualitative findings appear to be robust to the outliers in the VAR residual distributions.

Table 7.8: Robust Estimation: t-Statistic of Permanent and Temporary Components in Real Stock Prices

Decomposition by		$(1-L)q_t = \alpha q_{i,t} + \varepsilon_t$,	i=P,T,D
RALS	(a)	$(1-L)q_t = 0.99\ q_{T,t}$	R^2=0.30
		(0.07)	SSE=0.57
		[13.67]	DW=1.76
	(b)	$(1-L)q_t = 0.99\ q_{P,t}$	R^2=0.66
		(0.03)	SSE=0.27
		[29.45]	DW=2.04
	(c)	$(1-L)q_t = 0.75\ q_{D,t}$	R^2=0.04
		(0.19)	SSE=0.78
		[3.88]	DW=1.88
LAD	(a)	$(1-L)q_t = 0.92\ q_{T,t}$	R^2=0.40
		(0.06)	SSE=0.50
		[16.28]	DW=1.81
	(b)	$(1-L)q_t = 0.93\ q_{P,t}$	R^2=0.55
		(0.04)	SSE=0.38
		[22.21]	DW=2.08
	(c)	$(1-L)q_t = 0.87\ q_{D,t}$	R^2=0.05
		(0.22)	SSE=0.77
		[3.95]	DW=1.91

Notes: $q_{T,t}$ is the temporary component of real stock price movements, $q_{P,t}$ is the permanent component, and $q_{D,t}$ is the deterministic component. L is the lag operator. Estimation is by ordinary least squares. Figures in parentheses denote estimated standard errors. Figures in brackets denote standard t-statistics. The sample period is 1957:1-1995:11.

Figure 7.5: Impulse Response Functions: LAD and RALS

United States, 1957:1 - 1995:11

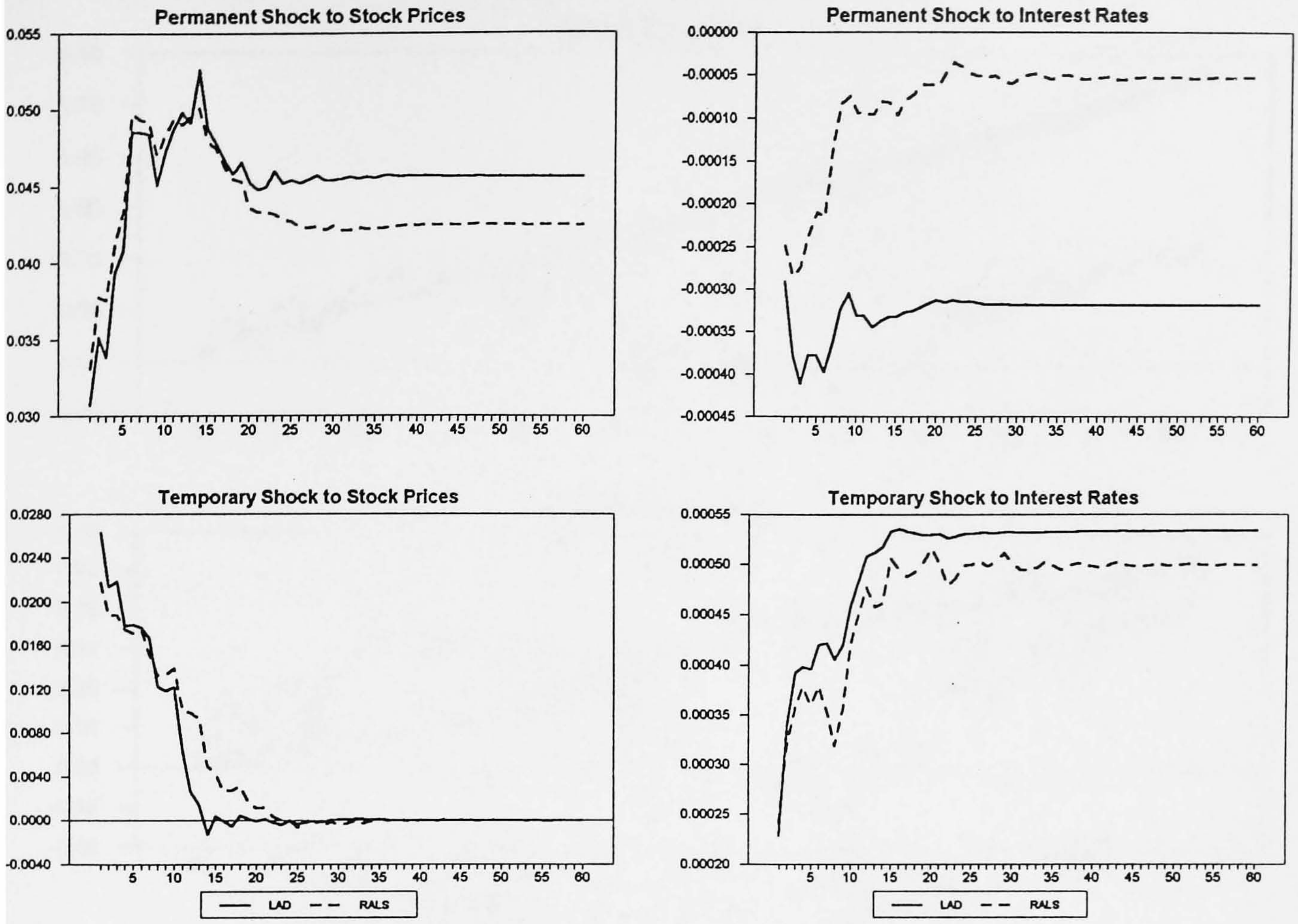
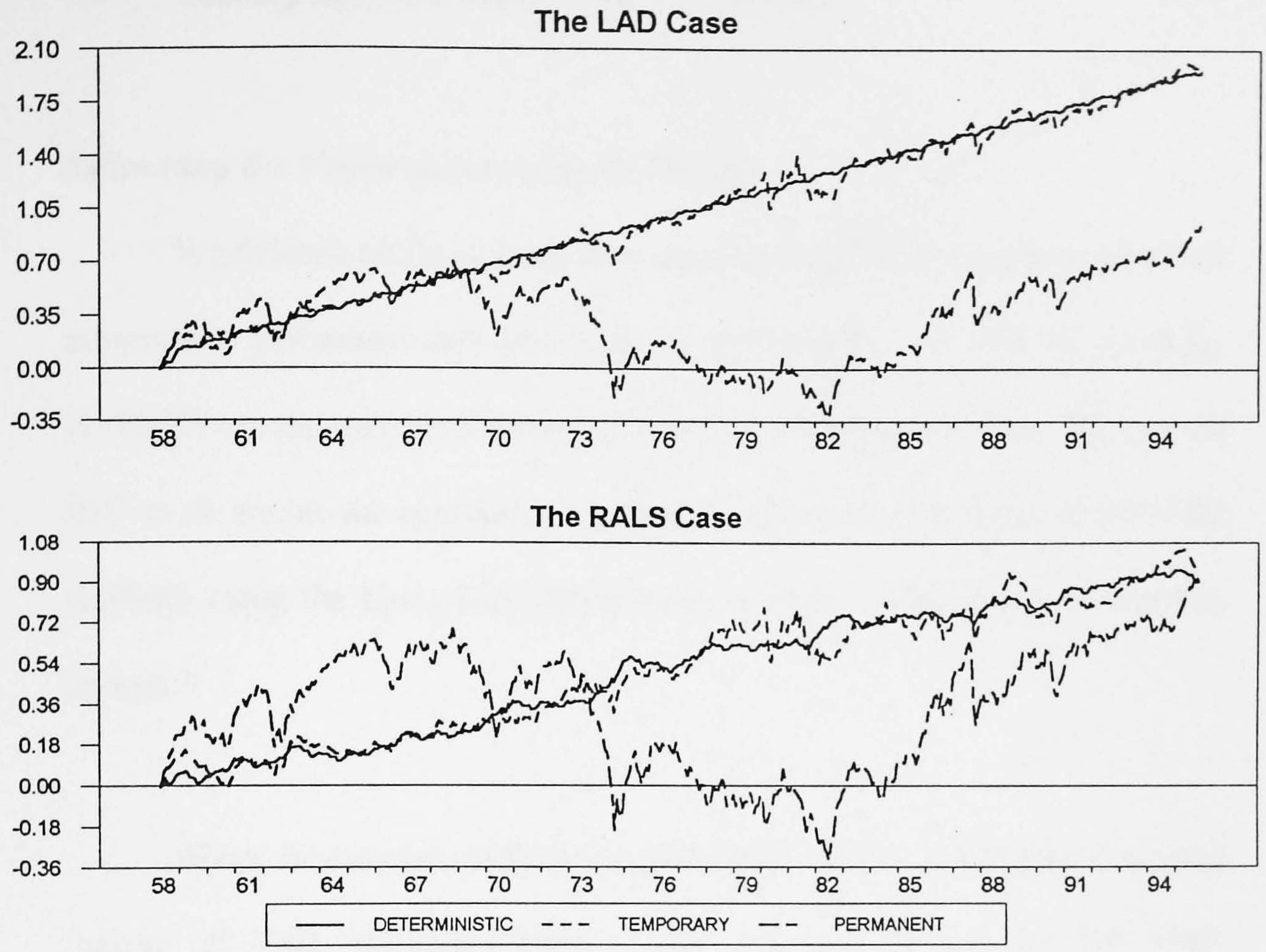


Figure 7.6: Components of Real Stock Prices

United States, 1957:1-1995:11



7.4 Decomposing UK Stock Price Movements

Estimating the Vector Autoregressive Process

We follow a similar procedure in decomposing UK stock prices into their temporary, permanent and deterministic components. A VAR of $[(1-L)q_t \; (1-L)r_t]'$ was estimated preliminary to effecting the decomposition. We use the BIC to determine the appropriate lag depth and test the whiteness of the VAR residuals using the Ljung-Box portmanteau statistic. A lag depth of one was chosen.[61]

Given the estimates of the VAR parameters (Table 7.9) and the covariance matrix of VAR residuals (Table 7.10), we then carried out the VAR decomposition. The estimated A(0) matrix (Table 7.11) is used to calculate the impulse response functions and estimate the innovations to real stock prices (these are presented in Figures 7.7 and 7.8). The cumulative impulse response functions are reported in Figure 7.7. The temporary shock is not persistent with a half-life of one month. A permanent shock to real stock prices increases stock prices for the first two months and stabilises at that level. A permanent shock to interest rates decreases interest rates, whereas a temporary shock increases interest rates.

Figure 7.8 illustrates the three components of real stock prices - temporary, permanent and deterministic. The plot line labelled deterministic

[61]The AIC also chose a lag length of one.

components are the trend and seasonal elements of real stock prices; the line labelled temporary component adds the temporary innovations to the deterministic component; and the line labelled permanent component adds the permanent innovations to the temporary component. Thus, the difference between the deterministic component and the temporary component lines measures the temporary innovations in real stock prices over the period. Similarly, the difference between the temporary component and the permanent component lines measures the permanent innovations in real stock prices.

The temporary component reported in Figure 7.8 indicates that the temporary innovations are small and stationary around the deterministic component. Formally, at the one-month horizon 7 percent of the forecast error variance in real stock prices is due to temporary innovations (see Table 7.12). The forecast error variance increases to 10 percent in the long run. The size of this temporary component is small when compared to US studies (Fama and French, 1988; Cochrane, 1994; Lee, 1995). International and UK studies on mean-reverting stock prices offer a limited direct comparison. Poterba and Summers (1988) and Cochran, *et al.* (1993) suggest (without directly calculating) the mean-reverting component for UK stock prices is quite similar in size to US stock prices, at around 12 percent for 8-year horizon. However, Mills (1991, 1995) and Cochran and DeFina (1995) estimate the variance ratio for UK stock prices in excess of unity and, thus, supports the hypothesis that UK stock prices are mean averting. As mentioned above, the variance ratio and the regression-based approaches have low power (see Richardson and Stock, 1989; Kim *et al.*, 1991;

Richardson, 1993; Mills, 1995).

Since in the VAR decomposition, by construction, $x_t = [(1-L)q_t\ (1-l)r_t]'$ is composed of three orthogonal shocks,[62,63] the t-statistics obtained from regressing the change in real stock prices, $(1-L)q_t$, onto each of these components in turn provides a test of the statistical significance of each component. Furthermore, the R^2s associated with each least squares regression estimate the proportion of total variation in real stock returns explained by each component.

Table 7.13 reports that the temporary component in real stock prices is statistically significant at standard significance levels. The estimated t-statistic has a value of 6.14. This significance of a mean-reverting component of UK stock prices is consistent with the evidence reported in Poterba and Summers (1988) and Cochran, *et al.* (1993). Although the size of the temporary component is somewhat smaller than that reported in many of the US studies there are a number of contributing factors; the power of alternative tests and, for example, Kim *et al.* (1991) suggest that mean reversion is a feature of the pre-war but not post-war environment. Other factors that contribute to a smaller temporary component

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[62] The permanent component, $x_{P,t}$, the temporary component, $x_{T,t}$, and the deterministic (trend and seasonal) component, $x_{E,t}$.

[63] The orthogonality of the shocks to stock prices can be tested by regressing one shock on the other shock, for the UK:

$$q_{T,t} = \underset{\substack{(0.0177)\\ [-0.0687]}}{-0.0012}\, q_{P,t} \qquad R^2 = 0.0000 \quad SSE = 0.1297 \quad DW = 2.71$$

found in UK stock prices include institutional factors and periodicity chosen to estimate the temporary component. Moreover, recent studies that have examined international stock markets have reported a smaller temporary component than US counterpart studies (Cochran, *et al.*, 1993; Mills, 1995).

Table 7.9: VAR Parameter Estimates: OLS, LAD and RALS

		OLS	LAD	RALS
$(1\text{-}L)q_t$	$(1\text{-}L)q_{t\text{-}1}$	0.08333	0.09955*	0.10769*
		(0.05273)	(0.04050)	(0.0462)
	$(1\text{-}L)r_{t\text{-}1}$	-28.65800*	-30.3500*	-28.13956*
		(6.66436)	(4.69034)	(5.8316)
Statistics:				
Number of Usable Obs.		364	364	364
R^2		0.12	0.07	0.39
Sum of Squared Errors		1.18	1.19	0.77
Ljung-Box Q(36)		45.30 [0.14]		31.48 [0.68]
Jarque-Bera				774.65
Skewness				-0.11
Kurtosis				7.43
Efficiency ($\hat{\eta}$)				0.79

		OLS	LAD	RALS
$(1\text{-}L)r_t$	$(1\text{-}L)q_{t\text{-}1}$	0.0005112	0.0003214	0.0006448
		(0.0004211)	(0.0002935)	(0.0003693)
	$(1\text{-}L)r_{t\text{-}1}$	0.2221706*	0.230463*	0.3439*
		(0.0532157)	(0.033988)	(0.0476)
Statistics:				
Number of Usable Obs.		364	364	364
R^2		0.10	0.05	0.41
Sum of Squared Errors		0.00	0.00	0.00
Ljung-Box Q(36)		31.17 [0.70]		37.48 [0.40]
Jarque-Bera				809.74
Skewness				0.96
Kurtosis				7.35
Efficiency ($\hat{\eta}$)				0.79

Notes: The figures in parenthesis denote estimated standard errors. The deterministic parameters are not reported. The Jarque-Bera is asymptotically distributed as $\chi^2(2)$ and the critical value is 5.991 at the 5% level of significance. The skewness and Kurtosis statistics are from Kendall and Stuart (1958) and the critical values are 0.22 and 0.45 at the 5% level of significance, respectively. An asterisk denotes significantly different from zero at the 5% level of significance. The statistic $\hat{\eta}$ measures efficiency gain from employing RALS as opposed to OLS. The sample period is 1965:1-1995:6.

Table 7.10: Covariance Matrix of VAR Residuals - UK

OLS	$\begin{bmatrix} 3.2546e-3 & -4.0716e-6 \\ -4.0716e-6 & 2.0752e-7 \end{bmatrix}$
LAD	$\begin{bmatrix} 3.2649e-3 & -4.0936e-6 \\ -4.0936e-6 & 2.0818e-7 \end{bmatrix}$
RALS	$\begin{bmatrix} 3.2631e-3 & -4.0774e-6 \\ -4.0774e-6 & 2.0803e-7 \end{bmatrix}$

Table 7.11: A(0) Matrix - UK

OLS	$\begin{bmatrix} 0.0153 & 0.0550 \\ 4.1440e-4 & -1.8918e-4 \end{bmatrix}$
LAD	$\begin{bmatrix} 0.0162 & 0.0548 \\ 4.1168e-4 & -1.9673e-4 \end{bmatrix}$
RALS	$\begin{bmatrix} 0.0175 & 0.0544 \\ 4.0710e-4 & -2.0565e-4 \end{bmatrix}$

Table 7.12: Forecast Error Variance Decomposition

Percentage of Variance Due to Temporary Shocks:

Horizon (months)	Interest Rates	Stock Prices
1	82.75	7.16
2	83.47	9.97
3	83.49	10.33
4	83.49	10.34
5	83.49	10.34
6	83.49	10.34
12	83.49	10.34
24	83.49	10.34
36	83.49	10.34

Percentage of Variance Due to Permanent Shocks:

Horizon (months)	Interest Rates	Stock Prices
1	20.97	92.84
2	20.70	90.03
3	21.18	89.67
4	21.34	89.66
5	21.33	89.66
6	21.45	89.66
12	21.74	89.66
24	22.65	89.66
36	22.66	89.66

Notes: Estimation is by ordinary least squares. The sample period is 1965:1-1995:6.

Table 7.13: t-Statistic of Permanent and Temporary Components in Real Stock Prices

Decomposition by		$(1\text{-}L)q_t = \alpha q_{i,t} + \varepsilon_t$,	i=P,T,D
OLS	(a)	$(1\text{-}L)q_t = 0.99\ q_{T,t}$ (0.16) [6.14]	R^2=0.09 SSE=1.22 DW=1.65
	(b)	$(1\text{-}L)q_t = 1.00\ q_{P,t}$ (0.02) [44.64]	R^2=0.85 SSE=0.21 DW=2.43
	(c)	$(1\text{-}L)q_t = 1.00\ q_{D,t}$ (0.21) [4.72]	R^2=0.06 SSE=1.27 DW=1.74

Notes: $q_{T,t}$ is the temporary component of real stock price movements, $q_{P,t}$ is the permanent component, and $q_{D,t}$ is the deterministic component. L is the lag operator. Estimation is by ordinary least squares. Figures in parentheses denote estimated standard errors. Figures in brackets denote standard t-statistics. The sample period is 1965:1-1995:6.

Figure 7.7: Cumulative Impulse Response Functions

United Kingdom, 1965:1 - 1995:6

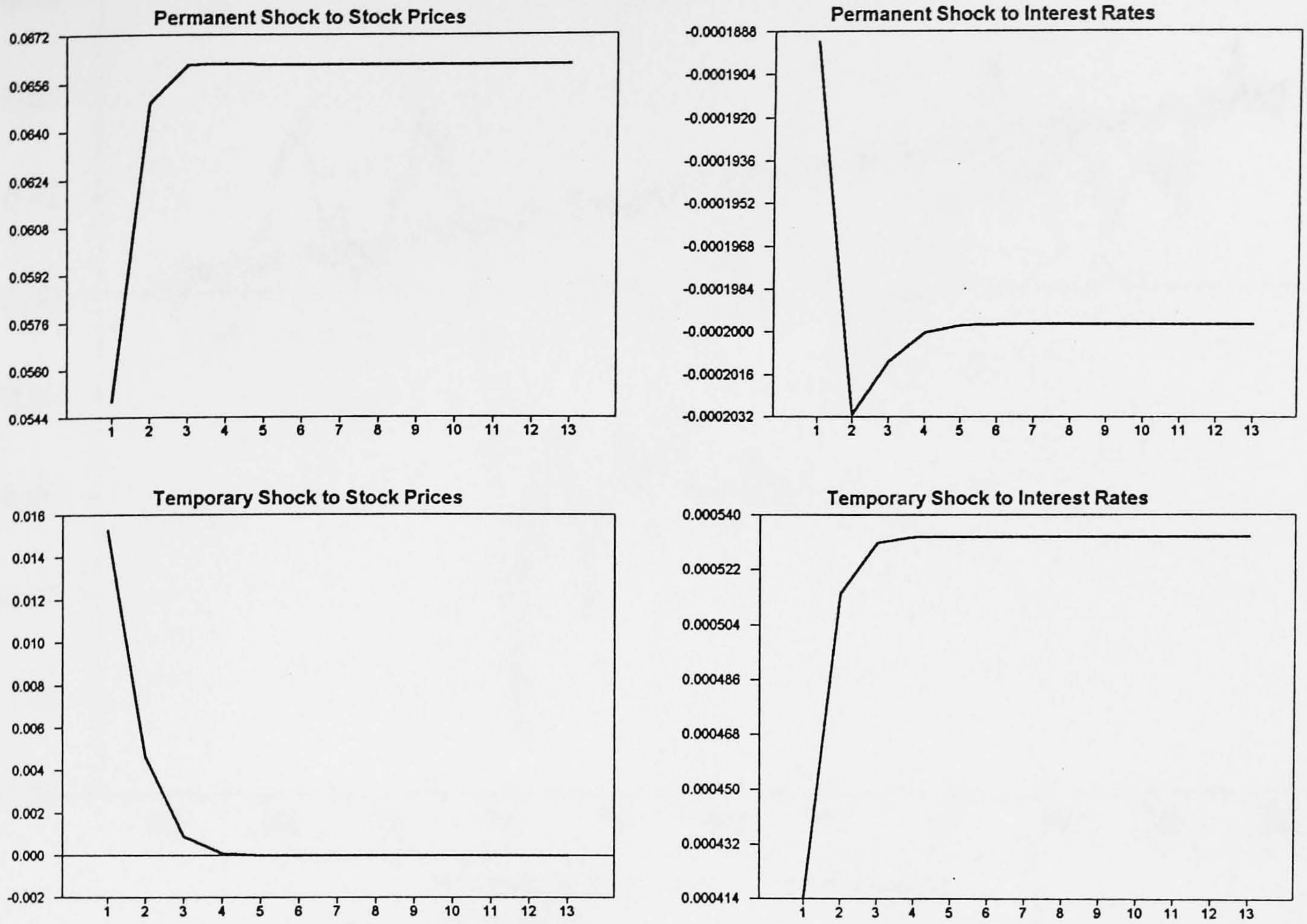
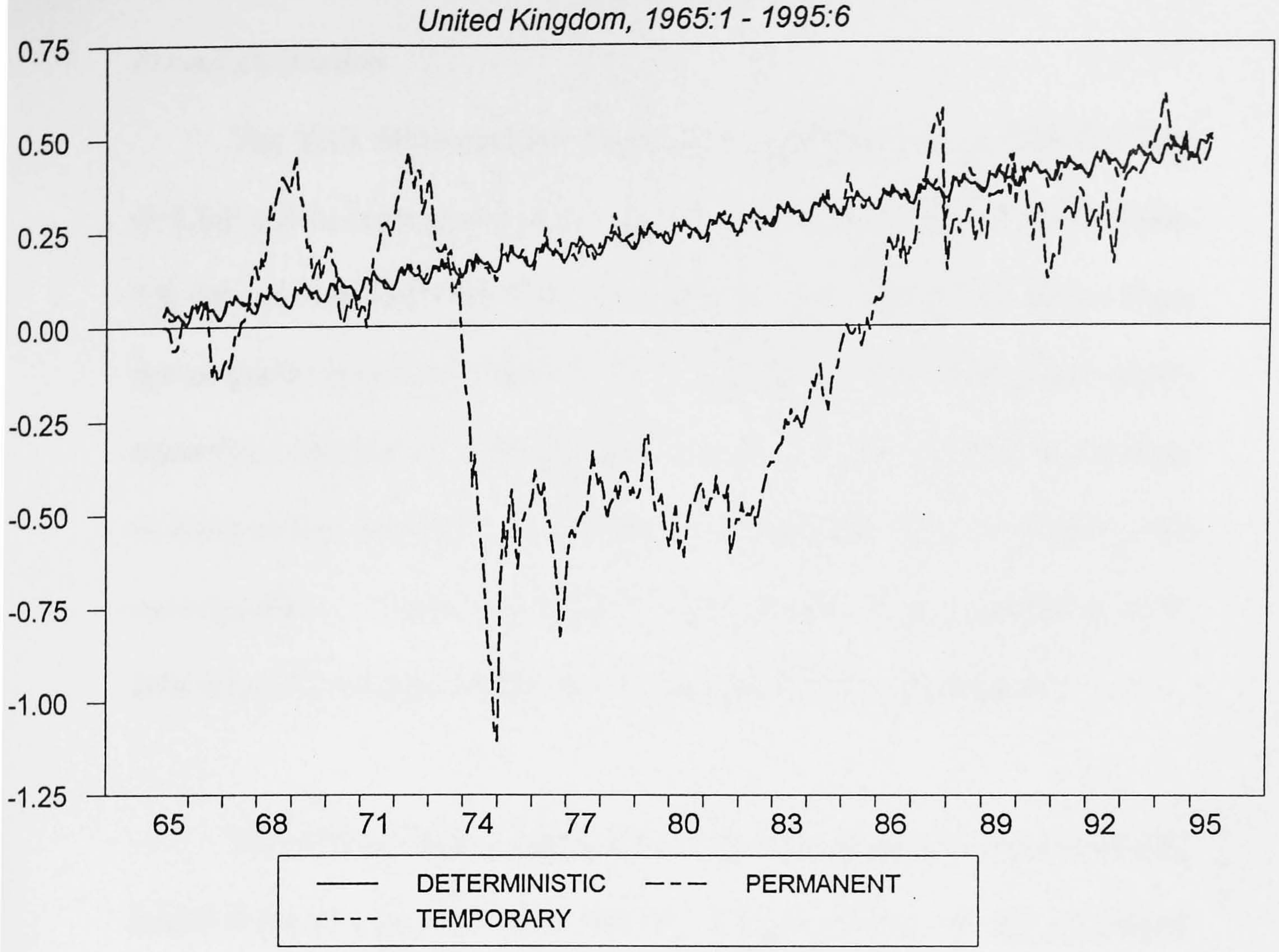


Figure 7.8: Components of Real Stock Prices



Robust Estimation

The VAR decomposition requires the parameters of the VAR $[(1-L)q_t\ (1-L)r_t]'$ and the covariance matrix of the VAR residuals.[64] As reported in Table 7.9, the residuals of the VAR estimated by LS are non-normal; the Jarque-Bera non-normality statistic is 774.65 and 809.74 for the stock price and interest rate regression, respectively. This suggests that there is a substantial gain in efficiency in using robust estimation procedures to estimate the VAR to effecting the decomposition. The RALS efficiency gain statistic $\hat{\eta}$ is estimated at 0.79, indicating efficiency gains of around 21 percent, for both regressions.[65]

The VAR parameter estimates from the three estimation procedures, LS, RALS and LAD, are shown in Table 7.9. These estimates and the covariance matrix of the residuals (see Table 7.10) are used to calculate the elements in the A(0) matrix (see Table 7.11). As in the LS case, the estimated A(0) matrix is used to estimate the innovations in real stock prices and are presented in Figures 7.9 and 7.10. The RALS and LAD estimated temporary and permanent components in real stock prices are similar to the those estimated using LS (as presented in Figure 7.7 and 7.8). The size of the temporary component is relatively small. The robust estimation procedures tends to slightly increase the size of the temporary

[64]Before we estimated the VAR, $(1-L)q_t$ and $(1-L)r_t$ were deseasonalised by regressing $(1-L)q_t$ (and similarly for interest rates) onto seasonal dummies and taking the residuals as the deseasonalised series.

[65]The efficiency gain appears to be primarily due to the fourth moment. Skewness statistics are -0.11 (insignificantly different from zero) and 0.96, and kurtosis statistics 7.43 and 7.35, for stock price and interest rate regression, respectively.

component - the non-normal distribution properties of VAR residuals does not account for the finding of a mean-reverting component in UK stock prices.

In testing the size and significance of the mean-reverting component we repeat the procedure employed in the LS case: each component of $(1-L)q_t$ as generated by the LAD and RALS technique is regressed on the change in real stock prices using ordinary least squares. The results, reported in Table 7.14, show that the temporary component is around the same size and of similar significant than the LS estimation. The two robust estimation procedures yields a slightly differing temporary component - the RALS estimates a temporary component of 11 percent, whereas for the LAD procedure 10 percent of the error variance in real stock prices due to temporary innovations - both are significant at standard significance levels.

Table 7.14: Robust Estimation: t-Statistic of Permanent and Temporary Components in Real Stock Prices

Decomposition by		$(1-L)q_t = \alpha q_{i,t} + \varepsilon_t$,	i=P,T,D
RALS	(a)	$(1-L)q_t = 0.98\ q_{T,t}$	R^2=0.11
		(0.15)	SSE=1.20
		[6.67]	DW=1.64
	(b)	$(1-L)q_t = 0.99\ q_{P,t}$	R^2=0.83
		(0.02)	SSE=0.23
		[41.88]	DW=2.44
	(c)	$(1-L)q_t = 0.93\ q_{D,t}$	R^2=0.06
		(0.21)	SSE=1.28
		[4.46]	DW=1.69
LAD	(a)	$(1-L)q_t = 0.98\ q_{T,t}$	R^2=0.10
		(0.15)	SSE=1.21
		[6.45]	DW=1.65
	(b)	$(1-L)q_t = 0.99\ q_{P,t}$	R^2=0.83
		(0.02)	SSE=0.24
		[41.11]	DW=2.26
	(c)	$(1-L)q_t = 0.85\ q_{D,t}$	R^2=0.06
		(0.19)	SSE=1.28
		[4.40]	DW=1.73

Notes: $q_{T,t}$ is the temporary component of real stock price movements, $q_{P,t}$ is the permanent component, and $q_{D,t}$ is the deterministic component. L is the lag operator. Estimation is by ordinary least squares. Figures in parentheses denote estimated standard errors. Figures in brackets denote standard t-statistics. The sample period is 1965:1-1995:6.

Figure 7.9: Impulse Response Functions: LAD and RALS

United Kingdom, 1965:1 - 1995:6

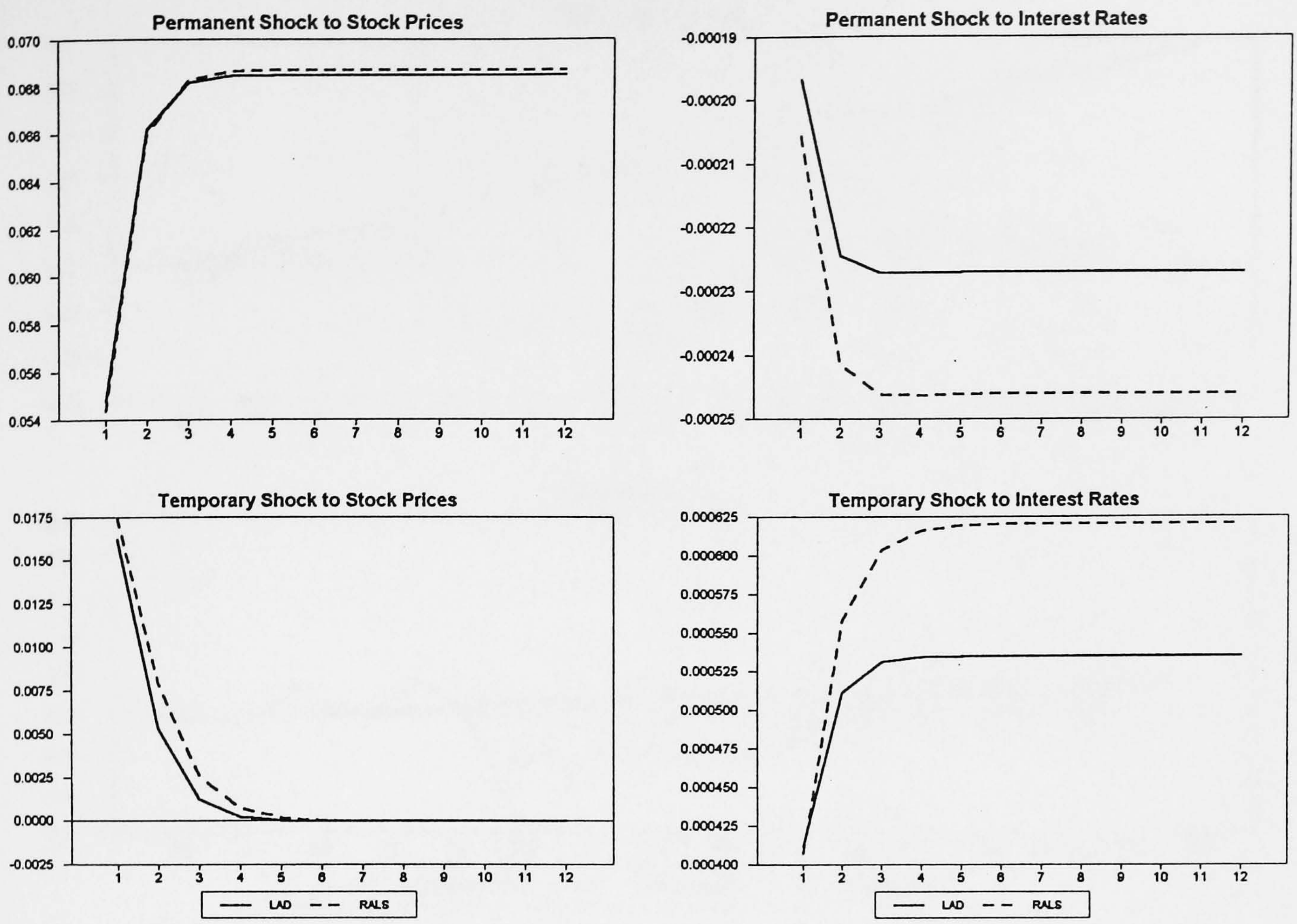
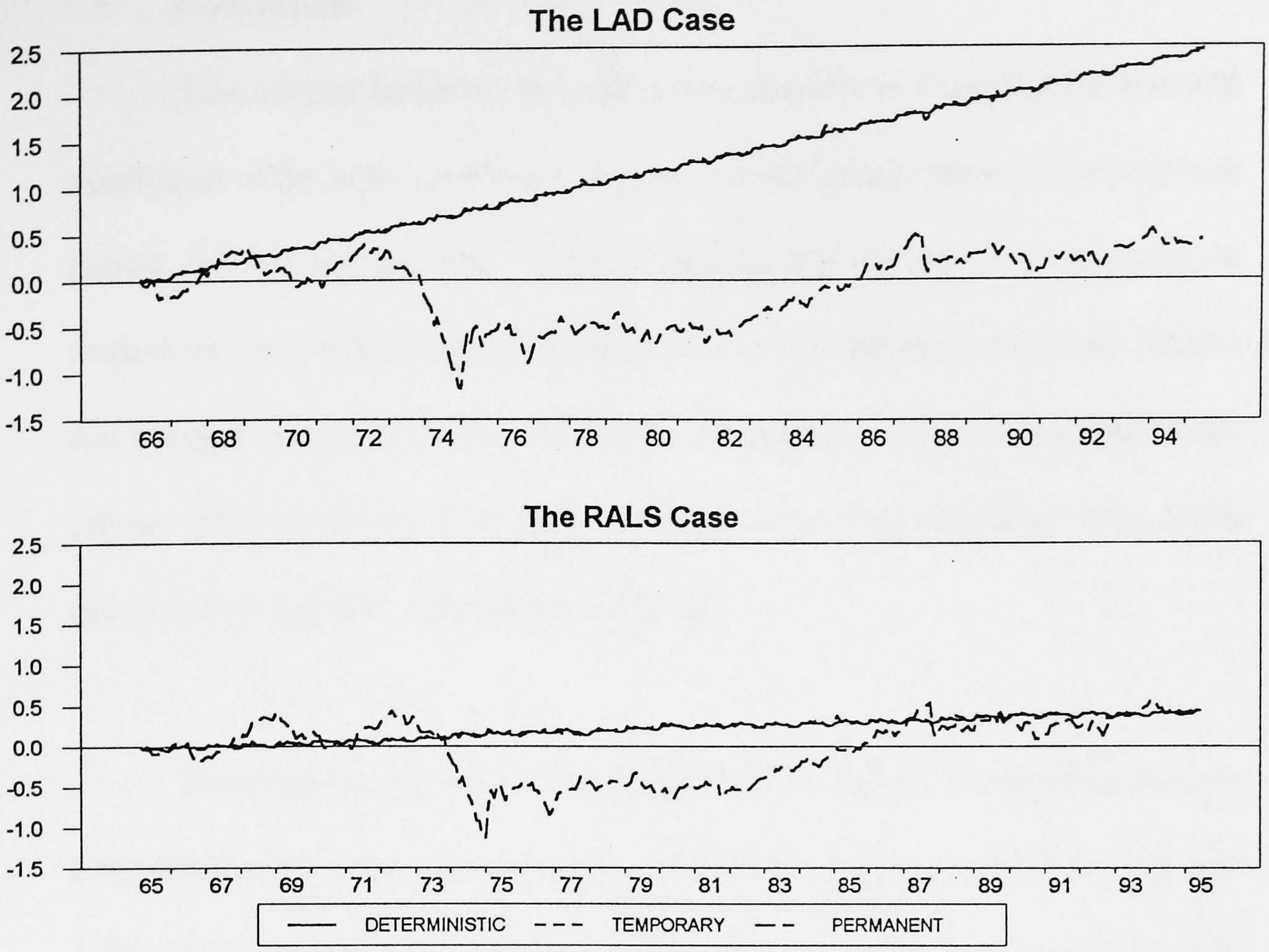


Figure 7.10: Components of Real Stock Prices

United Kingdom, 1965:1-1995:6



7.5 Conclusion

This chapter builds on the earlier two chapters in exploring the size and significance of the mean-reverting component in real stock prices in the post-war period, for the US and UK. Using a multivariate innovation decomposition method we have investigated the dynamic relationship between real stock returns and changes in interest rates to estimate the temporary component of real stock prices. The underlying VAR in the decomposition was estimated using three estimation procedures: LS, RALS and LAD.

The evidence supports the hypothesis that US and UK stock prices contain a statistically significant mean-reverting component, explaining around 25%, and 10%, of the variation in real stock price movements, for US and UK prices, respectively. Therefore, returns are to some extent predictable (see, for example, Pesaran and Timmermann, 1995). This evidence supports the earlier results from the previous two chapters.

The smaller mean-reverting, albeit statistically significant, component in UK stock prices is consistent with international studies. There is strong evidence, especially that of previous researchers who have used vector autoregressive techniques to decompose stock prices, that US stock prices contain a large mean-reverting component and our findings support this hypothesis. In contrast, the previous results for UK stock prices which rely on variance ratio and the related regression-based tests which generate contrasting findings dependent on the sample period and the distribution properties of the variance ratio statistic. For example, Mills(1991, 1995) and Cochran and DeFina (1995) find that post-war UK stock prices contain a mean-averting component, while Poterba and Summers (1988) find a significant mean-reverting component that includes the WW II period.

The VAR approach we use is not subject to the overlapping data problems encountered in the long-horizon approaches and, in contrast to Mills (1991, 1995) and Cochran and DeFina (1995), identifies a significant mean-reverting component in UK stock prices that explains about 10 percent of stock price movements. It is noticeable that temporary shocks to UK real stock prices have a half-life of only one month - thus, the mean-reverting component is not persistent and is less likely to be identified using either a regression-based or a variance-ratio approach. Whereas, temporary shocks to US real stock prices tend to be quite persistent, with a half-life of seven months.

The findings are robust to alternative estimation procedures designed to allow for non-Gaussian disturbances. The RALS estimation procedure yields substantial efficiency gains of over 20 percent. The non-normality in the least squares VAR residuals causes the size of the mean-reverting component to be underestimated. The RALS procedure estimates that, for the US, 30 percent of the variation in real stock price movements can be explained by temporary shocks. The LAD procedure estimates that 40 percent of the variation in real stock price movements can be explained by the mean-reverting component. The RALS and LAD procedures estimate only a slightly higher mean-reverting component that the LS procedure. Thus, the LS qualitative findings appear to be robust to the outliers in the VAR residual distributions.

Evidence of a significant mean-reverting component in stock prices could be explained by the existence of speculative bubbles, fads or noise traders (Blanchard and Watson, 1982; Shiller, 1984; De Long *et al.*, 1990; Shleifer and Vishny, 1997). A practical implication for investors is that returns must be negatively serially correlated at some frequency. This suggests investors should use a portfolio strategy that includes equities that have recently declined in value. An extension to the present work is to examine the degree of predictability implied by the mean-reverting component.

Chapter 8

LITERATURE ON THE STOCK RETURN-INFLATION PUZZLE AND THE PROXY HYPOTHESIS

8.1 The Fisher Hypothesis

The influential work of Irving Fisher, *The Theory of Interest* (1930), is still the object of much debate, centred around the inflation-interest rate puzzle. "When the cost of living is not stable, the rate of interest takes the appreciation and depreciation into account to some extent, but only slightly and, in general, indirectly. That is, when prices are rising, the rate of interest tends to be high but not so high as it should be to compensate for the rise; and when prices are falling, the rate of interest tends to be low, but not so low as it should be to compensate for the fall" (p. 43). The hypothesis postulated by Fisher has taken many forms, including generalizing the relationship to all assets. It is the inflation-stock returns puzzle that we will empirically examine in Chapter 9.

The most common version of the Fisher hypothesis is that *ex ante* real rates of return are uncorrelated with expected inflation. "If men had perfect foresight, they would adjust the money interest rate so as exactly to counterbalance or offset the effect of changes in the price level, thus causing the real interest rate to remain unchanged at the normal rate". (Fisher, 1930, pp. 414-5). Therefore, assets are a hedge against inflation in the sense that expected nominal rates of return on assets move one-to-one with expected inflation. Fisher (1930) acknowledges that lack of foresight ("money illusion") would lead to a less-than-perfect positive correlation between nominal interest rates and the actual rate of inflation.

The dynamic effects of the inflation-interest rate relation are described by Fisher (1930) as price changes affecting interest rates via the volume of trade and the demand for loanable funds. "If the price level falls in such a way that they may expect for themselves a shrinking margin of profit, they will be cautious about borrowing unless interest falls, and this very unwillingness to borrow, lessening the demand in the money market, will tend to bring interest down. On the other hand, if inflation is going on, they will scent rising prices ahead and so rising money profits, and will be stimulated to borrow unless the rate of interest rises enough to discourage them, and their willingness to borrow will itself tend to raise interest" (p. 400). "The indirectness of the effect of changed purchasing power of money [on money rate of interest] comes largely through the intermediate steps which affect business profits and volume of trade, which in turn affect the demand for loans and the rate of interest. There is very little direct and conscious adjustment through foresight. Where such foresight is conspicuous, as in the final period of German inflation, there is less lag in the effects" (p. 494).

Fisher's (1930) work on interest rates is based on the view that the monetary and real sectors of the economy are independent. "Theoretically, the rate of interest should be subject to both a nominal and a real variation, the nominal variation being that connected with changes in the standard of value, and the real variation being connected with the other and deeper economic causes" (p.493). It is the independence of the monetary and real sectors that results in expected nominal interest rates (or rates of return on assets) moving one-for-one with expected inflation. That is, the real interest rate is unrelated to the monetary sector and is determined solely by real factors, e.g. productivity, time preference, and risk aversion. The hypothesis that prices have no real effects - money is neutral - does not exclude the fact that inflation and real output growth can be correlated via, for example, the money supply process (Fama, 1981; Cox, Ingersoll and Ross, 1985).

The Fisher hypothesis can be summarised in an equation: $r^* = r - \pi^e$, where r^* = real rate of interest, r = nominal rate of interest, and π^e = expected rate of inflation.[66] If r^* is constant then r and π^e are perfectly positively correlated, and the Fisher hypothesis is $dr/d\pi^e = 1$ or $dr^*/d\pi^e = 0$, where d is the differential operator. In order to test directly the Fisher hypothesis, a measure of inflation expectations is required. Previous studies assume either perfect foresight (the observed inflation rate), adaptive expectations (lagged inflation rates), rational expectations (instrumental variable estimation) or use survey data (for example, the Livingston survey of expected inflation). In terms of the true expected inflation, each of these approaches is subject to misspecification and therefore measurement error.

Tobin (1965) and Feldstein (1976) modify the Fisher hypothesis to account

[66]Fisher did not state that the expected real rate of interest must be constant.

for an interest insensitive demand for real money balances and taxes. Tobin argues that the nominal rate of interest rises by less than the rate of inflation because inflation reduces the demand for real money balances, increases capital intensity and lowers the real rate of return. Feldstein extends Tobin's argument by also including corporate and personal income taxes in the analysis. For example, with no change in capital intensity, a corporate tax cause the nominal rate of interest rises by more than the rate of inflation. Furthermore, real interest rates may either rise or fall depending on the difference between the corporate tax rate and the personal income tax rate.

8.2 Explaining the Stock Return-Inflation Puzzle

The traditional view that common stocks are a good hedge against inflation is not empirically supported. Post-war data for the US and other countries exhibits a significant negative correlation between inflation and real stock returns and between inflation and nominal stock prices[67]. Thus, real stock returns are not independent of inflation. This contradicts the Fisher model in which nominal asset returns move one-for-one with the rate of inflation so that real stock returns are determined by real factors independently of the rate of inflation.

In a pioneering paper, Fama (1981) sought to explain the stock return-inflation puzzle by hypothesizing that the negative correlation is induced by negative correlations between inflation and real activity together with a positive relationship between stock returns and real fundamentals. Fama (1981) explains the negative relation between stock returns and inflation using money demand theory.[68] An increase in expected future real activity leads to an increased demand for real money balances. The increased demand for real money balances, given the

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[67] See, for example, Jaffe and Mandelker (1976); Bodie (1976); Nelson (1976); Fama and Schwert (1977); Fama (1981); Geske and Roll (1983); Gultekin (1983a,b); Solnik (1983); Mandelker and Tandon (1985); Wahlroos and Berglund (1986); Lee (1989); Kaul (1987, 1990); Marshall (1992); Cochran and DeFina (1993); Graham (1996); Groenewold, O'Rourke and Thomas (1997).

[68] In a similar study to that of stock returns, Fama and Gibbons (1982) argue that the variation in expected real returns on Treasury bills "is more fundamentally due to the capital investment process than due to variation in expected inflation" (p. 298).

level of nominal money, results in a fall in the price level.[69] Furthermore, assuming stock prices are determined by expected future dividends and therefore, stock returns are related to expected real output growth in the economy (see, for example, Fama, 1990; Schwert, 1990b; Canova and De Nicolo, 1995),[70] then inflation will proxy for future real output growth, leading to the spurious finding of a negative correlation between stock returns and inflation. In effect, therefore, Fama's proxy hypothesis suggests that the apparent anomalous relationship between stock returns and inflation is simply proxying the positive relationship one would expect between stock prices and fundamentals. The negative relation disappears when you include both inflation and future real output as explanatory variables (Fama, 1981; Kaul, 1987).

A number of authors have concentrated on modelling the relationship between stock returns, inflation, real activity and monetary growth in a general-equilibrium or partial-equilibrium framework (see, for example, Danthine and Donaldson, 1986; Stulz, 1986; Marshall, 1992; Balkshi and Chen, 1996). These models follow from Fama's (1981) 'proxy hypothesis' according to which the negative relationship between inflation and stock returns reflects the fact that real

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[69]The reason why expected future output growth in the economy and inflation are negatively correlated may also be due to counter-cyclical monetary policy (Kaul, 1987).

[70]The relation between stock returns and expected future real output growth can be explained by a number of possibilities, for example, real output growth captures information about future cash flow to firms (Fama, 1981; Geske and Roll, 1983; Kaul, 1987), stock prices and production can respond together to other variables (Barro, 1990), and stock returns might cause changes in real activity (*ibid*).

activity is negatively related to inflation (through a quantity theoretic mechanism) and positively related to stock returns. Although these models provide a more formal treatment of the role of money (e.g., through cash-in-advance constraints or treating money as an asset), they are not constructed within the Fisherian framework - the models violate the hypothesis of independence of the real and monetary sectors of the economy - and are, therefore, not strictly appropriate to examine the Fisher hypothesis.

From Danthine and Donaldson (1986), Stulz (1986), Marshall (1992) and Bakshi and Chen (1996) we can identify a number of common findings that are consistent with previous empirical studies: first, stocks do not offer a hedge against that portion of inflation caused by fluctuations in real economic activity; second, stocks offer a good hedge over the long run against purely monetary inflations; and third, it is the interdependence of economic variables that provides the explanation of the negative stock return-inflation relationship.[71] A drawback of these equilibrium models is that they tend to be highly stylized and the correlations predicted by them bare little resemblance to actual data. This brings into question their ability to explain the stock return-inflation phenomenon.

More recently, Boudoukh, Richardson and Whitelaw (1994) show that the coefficient from regressing stock returns on expected inflation is not necessarily

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[71]Balduzzi (1995) using a five variable VAR finds evidence that inflation and stock returns exhibit the strongest negative correlation when there is an inflation innovation.

equal to one because expected inflation may be partly proxying for expectations about future real rates. Furthermore, the sign and size of the coefficient is determined by the covariance between expected inflation and expected future values of real variables - which is expected to be negative. Thus, in a money-neutral setting, the negative correlation coefficient is consistent with the Fisher hypothesis. Boudoukh *et al.* (1994) use expectations about future dividend growth rates and price-dividend ratios as a proxy for expected future real variables. Since, through time, expected dividend growth rates differ across industries, this forms the basis for their cross-sectional study of the Fisher hypothesis applied to US industry-sorted stock returns and expected inflation. Stock returns of noncyclical industries tend to covary positively with expected inflation, while the reverse holds for cyclical industries. This finding is consistent with Fama (1981) and Kaul (1987).

The hypothesis that expected future output growth in the economy and inflation are negatively correlated is due to counter-cyclical monetary policy (Kaul, 1987, 1990).[72] Periods when monetary policy were counter-cyclical - according to Kaul this is the post-World War II period - exhibit a stronger negative relationship. There is a close link between the monetary policy of the Federal Reserve and the relation between stock returns and inflation. Graham (1996) offers additional support for this hypothesis.

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[72]This is consistent with Fama (1981) proxy hypothesis.

An alternative perspective to that of Fama's (1981) explanation of the negative relation between stock returns and inflation is provided by Geske and Roll (1983) and centres on the finding that there is a causal relation between stock returns and inflation.[73] Geske and Roll (1983) argue that stock returns Granger cause expected inflation through a chain of macroeconomic events. The argument is based on the response of money supply to changes in anticipated real activity rather than the money demand theory used by Fama. Assuming that changes in government revenue are negatively related to changes in real activity and government expenditures are fixed, then changes in revenue lead to opposite changes in the government's deficit. If the deficit is monetized, the change in money supply causes an increase in inflation. If the deficit is not monetized, then real interest rates increases, which may increase nominal interest rates - a proxy for expected inflation. As in the case of Fama (1981), agents anticipate this process, and stock returns signal changes in expected inflation.

If stock returns Granger cause expected inflation, and there exists a negative relation between stock returns and inflation, then the proxy hypothesis is explained by the money supply theory offered by Geske and Roll. The absence

[73]If the negative relation between real stock returns and inflation is non-spurious, evidence of a causal relation from inflation to real stock returns could imply non-neutrality of money. A number of studies suggest alternative theories that could explain this finding, these include the riskiness of stocks (Malkiel, 1979; Pindyck, 1984), money illusion (Modigliani and Cohn, 1979), the tax system (Summers, 1981), and the Mundell-Tobin effect (Ram and Spencer, 1983).

of the causal relation supports the Fama interpretation.[74] Empirical evidence is mixed, for example, Solnik (1983) and Titman and Warga (1989) provide consistent support for Geske and Roll's hypothesis, Cozier and Rahman (1988) find, for Canada, no Granger causal relation between inflation and real stock returns, James, Koreisha and Partch (1985) strongly support the hypothesis that stock returns Granger causes expected inflation and, in contrast, Lee (1992) supports Fama (1981) and reports that, with interest rates included in the VAR, stock returns explain little variation in inflation. Furthermore, Lee (1992) highlights that the key feature that differentiates his results from James *et al.* (1985) is the inclusion of interest rates in the VAR.[75] More recently, Graham (1996) finds that the negative relation between stock returns and inflation is not connected to the degree of debt monetization. Balduzzi (1995), using a five variable VAR, finds evidence that the interest rate explains a large fraction of the negative correlation

There are a number of alternative competing theories to Fama (1981) and

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[74]In contrast, Ram and Spencer (1983) find evidence of unidirectional causality from inflation to stock returns. This causal relation can be explained by the Mundell-Tobin effect - the combination of the Phillips curve and a negative output-stock return correlation. However, more recent studies do not support the hypothesis that inflation (Granger) causes stock returns.

[75]Lee (1989) estimate a nonlinear stochastic equilibrium model to observe the empirical relations between inflation and stock returns. The model generates correlation signs consistent with Fama (1981) and similar to actual data. Forecast error variances reveal a similar pattern to Lee (1992); stock returns appears to be Granger-causally prior and explains substantial fraction of the variation in real activity but does not explain variation in inflation. Furthermore, the model highlights the importance of the interest rate variable in explaining variation in inflation.

Geske and Roll (1983) that explain the negative relation between inflation and real activity. For example, Feldstein (1980a,b) argues that the negative relation between inflation and real activity can be explained by the tax burden theory, that is inflation increases the effective tax rate and hence depresses real activity. Malkiel (1979), Evans (1991b) and Evans and Wachtel (1993) argue that inflation uncertainty is positively related to the level of inflation, and that inflation uncertainty depresses future output because it discourages investment. In a related study, Kaul and Seyhun (1990) shows that, together with the money demand process suggested by Fama (1981), the negative relation between stock returns and inflation can be explained by the supply side shocks reflected in relative price variability particularly the OPEC oil crises of 1973-74. The relative price variability adversely affect output and stock returns. Therefore, the negative relation between stock returns and inflation proxy for the negative effects of relative price variability on the stock market.

Boudoukh and Richardson (1993) have assessed the stock return-inflation relationship in terms of a long-horizon perspective.[76] Using two centuries of annual data, they find, for a 5-year horizon, that there is a significant positive relationship between inflation and nominal stock returns.[77] This finding is horizon

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[76]Evans and Lewis (1995) using a Markov switching model and cointegration techniques examines the long-run relationship between nominal interest rates and inflation. The findings support the Fisher hypothesis that (in the long run) nominal interest rates reflect expected inflation one-for-one.

[77]A one-for-one relationship between inflation and nominal stock returns is not statistically supported. Although, the *ex ante* results tend to provide tentative support for the Fisher hypothesis.

specific since a short-horizons produces contrary results. Boudoukh *et al.* (1994) reports a similar finding. The 1802-1990 period covers a number of structural changes in the series. Moreover, because Boudoukh and Richardson (1993) are constrained in dealing with this issue as the long-horizon regression approach requires a long period of data, they focus their analysis on the different empirical implications over short and long horizons.[78] These results have to be considered, however, in the context of the inclusion of the Great Depression period and possible measurement errors due to the use of pre-war data (Schwert, 1990a).

Although the majority of studies that have investigated the Fisher hypothesis are US based, there exists a large volume of international evidence, for example, Gultekin (1983a), Mandelker and Tandon (1985), Wahlroos and Berglund (1986) consider Finland, Kaul (1987, 1990), Cozier and Rahman (1988) consider Canada, Peel and Pope (1988) consider the UK, Alkhazali and Pyun (1997) provide evidence from the Pacific-Basin countries and Groenewold *et al.* (1997) consider Australia.

In the next chapter, we investigate the stock return-inflation puzzle in the context of a simple macroeconomic model involving overlapping wage contracts, which predicts that the negative covariation of real stock returns and inflation is due primarily to aggregate supply side (real productivity) shocks. We then investigate the empirical validity of this prediction by decomposing inflation into

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[78]The two sub-periods 1870-1990 (post-Civil War) and 1914-1990 (post-Federal Reserve) report similar results to the full sample period.

two counterfactual series, one due to monetary (aggregate demand) shocks and the other due to real productivity (aggregate supply) shocks.[79] The statistical significance of the empirical correlation between the counterfactual inflation series and stock returns can then be tested. In addition, we also test other predictions of our simple model concerning the correlation of stock returns and movements in real output due to aggregate demand and supply shocks, as well as the correlations between inflation and real output movements.

[79]In order to effect a decomposition of the output growth and inflation series into the components due to aggregate supply and demand shocks respectively, we employ a multivariate innovation decomposition method.

Chapter 9

ASSESSING THE STOCK RETURN-INFLATION PUZZLE: EVIDENCE FROM A MACRO MODEL AND EMPIRICAL FINDINGS

9.1 A Macro Model: Explaining the Relationship Between Stock Returns and Inflation

> "Theoretically, the rate of interest should be subject to both a nominal and a real variation, the nominal variation being that connected with changes in the standard of value, and the real variation being that connected with the other and deeper economic causes" (Fisher, 1930, p. 493).

In the traditional aggregate demand-aggregate supply (ADAS) model with a long-run vertical supply curve, aggregate demand innovations result in only a temporary rise in output, while aggregate supply innovations permanently affect the level of aggregate output. That is, in the long run, aggregate demand innovations raise the price level but not output.

The purpose of this section is to set up an illustrative model which is essentially neoclassical and Fisherian in structure - and which allows reasonably complex dynamics - in order to illustrate the pattern of covariances which one would expect to find between macroeconomic and financial time series alternatively stripped of their aggregate demand and aggregate supply components. The model captures the salient features of the relation between stock returns and inflation. This can therefore serve as a motivating vehicle for the empirical work which follows.

Consider the simple linear macro model that we outlined in Chapter 3, section 3.1. The macro model includes a stock price determination equation and a wage formation equation where wages are set in a two-period overlapping contracts framework. For ease of reading a concised version of the model is presented here. The model incorporates the salient features of the models of Fischer (1977), Blanchard (1981) and Blanchard and Quah (1989):

$$(9.1) \quad y_t = m_t - p_t + a\theta_t + \alpha\pi_t$$

$$(9.2) \quad y_t = n_t + \theta_t$$

$$(9.3) \quad p_t = w_t - \theta_t$$

$$(9.4) \quad w_t = w|\{E_{t-2}n_t = \bar{n}\}$$

$$(9.5) \quad \pi_t = \phi y_t$$

$$(9.6) \quad q_t = \pi_t + \sum_{j=0}^{\infty} \rho^j E_t \Delta\pi_{t+1+j} + k^*$$

where the permissible range of the parameter space is governed by:

$$(9.7) \qquad a > 0, \;\; 0 < \alpha < 1, \;\; 0 < \phi < 1, \;\; 0 < \rho \leq 1$$

The variables, y, m, p, w, n, and θ denote, respectively, the log of output, the money supply, the price level, the nominal wage, employment and productivity, respectively. The log of dividends on equities is represented by π; $\bar{n}$ represents full employment; and q is the log of the real price of equities.

Equation (9.1) represents the aggregate demand side of the economy; with aggregate demand a function of real balances, productivity and distributed profits. For generality, we follow Blanchard and Quah (1989) in allowing productivity to affect aggregate demand on the grounds that it is likely to affect investment, so that we expect $a>0$, although setting $a=0$ does not qualitatively alter the results. The production function, equation (9.2), relates output to the level of employment and productivity. Equation (9.3) states that the price level is a function of the nominal wage and productivity. The nominal wage (equation (9.4)), chosen two periods ahead, is set at the expected full employment level in a two-period overlapping contracts framework (Fischer, 1977). Equation (9.5) expresses log of real dividends (distributed profit) as a function of real output.

Equation (9.6) specifies the log of real stock prices as a linear function of the log of real dividends. Following Campbell and Shiller (1988a,b), the log of real stock prices is a log-linear approximation of the standard present value model of stock prices.[80] The equation says that the log real stock price at time t is determined by the log real dividend at time t, expected real dividend growth into the infinite future, and a constant. Future real dividend growth rates are discounted at the rate ρ^j, for $j=0,..,\infty$, where ρ is close to but a little smaller than (positive) unity. A detailed derivation of equation (9.6) is given in Chapter 3, Appendix 3.1.

[80]We assume the dividend enter the log dividend-price ratio, $\delta_t \equiv \pi_t - q_t$, in the current period t - that is, the dividend in period t is also known in period t.

To close the model, we assume that m and θ are determined as follows:

$$(9.8) \quad \theta_t = \theta_{t-1} + e_{s,t}$$

$$(9.9) \quad m_t = m_{t-1} + e_{d,t}$$

where e_d and e_s are serially uncorrelated and pairwise orthogonal demand and supply disturbances.

Solving the model for inflation and real output growth, results in:

$$(9.10) \quad \Delta p_t = e_{d,t-2} - e_{s,t} + (a + \alpha\phi)e_{s,t-2}$$

$$(9.11) \quad \Delta y_t = (1 - \alpha\phi)^{-1}(e_{d,t} - e_{d,t-2}) + (1 - \alpha\phi)^{-1}(1 + a)(e_{s,t} - e_{s,t-2}) + e_{s,t-2}$$

From (9.11), we see that aggregate demand disturbances have only short-run effects on real output - cancelling out after two periods. Aggregate demand shocks do, however, have both short- and long-run effects on prices (equation (9.10)): a one-standard deviation demand shock raises inflation after two periods, leaving prices permanently higher. Aggregate supply disturbances have both long-run and short-run effects on both prices and output. A one standard-deviation supply shock raises real output growth immediately and is only partially reversed two periods later, leaving output permanently higher (equation (9.11)). A one-standard deviation supply shock leads to an immediate fall in prices (equation (9.10)) through the cost-plus-mark-up pricing rule. The aggregate supply shock causes a shift along the aggregate demand curve, however, as investment demand

and consumption out of distributed profits rise and has an effect on prices once contracts are renegotiated two periods later - hence the positive third term on the right-hand side of (9.10). Aggregate supply shocks have a net long-run depressant effect on prices - the long-run aggregate demand curve is downward sloping - so long as $(a+\alpha\phi)<1$, which is plausible given the bounded permissible range of these parameters - see (9.7).

To examine how these disturbances affect real stock returns we solve for real stock prices in terms of aggregate supply and demand disturbances:

$$(9.12) \qquad \Delta q_t = \phi(1-\rho)(1-\alpha\phi)^{-1}[(e_{d,t}-e_{d,t-1}) + (1+a)(e_{s,t}-e_{s,t-1})] + \phi\rho(e_{s,t}-e_{s,t-1}) + \phi e_{s,t-1}$$

As in the case of real output, aggregate demand disturbances have only short-run effects on real stock prices. A positive one unit aggregate demand disturbance increases real stock prices in the same period and reduces real stock prices by an equal amount in the following period. However, a similar aggregate demand disturbances on real output takes an additional period to have a similar zero long-run effect. In this model aggregate demand disturbances have a more persistent effect on real output than real stock prices.[81] Similar ro real output, aggreagte supply disturbances have both short-run and long-run effects on real stock prices.

[81]This feature is consistent with the hypothesis that stock returns Granger-cause future real activity (see, for example, Fama, 1981; James *et al.*, 1985; Lee, 1992).

Given the parameter space (9.7), an aggregate demand disturbances increases real stock prices in the short run and, in the long run, real stock prices decline back to their original level. An aggregate supply disturbance increases real stock prices in the short run and declines by a fraction of this increase in the long run. The net long-run effect of an aggregate supply disturbance is an increase in real stock prices.

The solution to the stock return, inflation and real output growth equations is consistent with Blanchard (1981). "The stock market is not the "cause" of the increase in output, no more than the increase in output is the cause of the initial stock market change. They are both the results of changes in policy. .....Although .... the change in the stock market and the resulting increase in output will precede the change in policy, they are still caused by it" (p. 141).

The covariance between real stock returns and inflation is obtained from equations (9.10) and (9.12), where the aggregate supply and demand disturbances are serially uncorrelated. The covariance between changes in stock prices and that part of inflation due entirely to supply shocks is given by:

$$(9.13) \quad \mathrm{Cov}(\Delta q_t, \Delta^s p_t) \;=\; -\left[\frac{\phi(1+a)(1+\rho)}{(1-\alpha\phi)} + \phi\rho\right] \;<\; 0$$

where $\Delta^s x_t$ denotes that part of the series Δx_t due only to aggregate supply shocks, for x=p,y. Inflation and real stock returns are expectd to be negatively correlated, given reasonable parameter values for a, α, ρ, and ϕ as identified by (9.7).

Therefore, a positive supply disturbance contemporaneously increases stock prices and reduces inflation.

Also, from (9.10) and (9.12) we can see that, in the absence of aggregate supply shocks to inflation, real stock returns are orthogonal to inflation - their covariance is zero.[82]

$$(9.14) \quad \mathrm{Cov}(\Delta q_t, \Delta^d p_t) = 0$$

where $\Delta^d x_t$ denotes that part of the series Δx_t due only to aggregate demand shocks, for x=p,y.

Since previous results (Fama, 1981; Geske and Roll, 1983; Kaul, 1987; Barro, 1990; Fama, 1990) indicate that real activity has a central role in any story about the variation of returns, we examine the relations between returns and real activity in detail. The covariance between real stock returns and real output growth can then be calculated from (9.11) and (9.12). In the absent of aggregate demand shocks, the covariance is given by:

$$(9.15) \; \mathrm{Cov}(\Delta q_t, \Delta^s y_t) = \left[\frac{1+a}{1-\alpha\phi}\right]\left[\frac{\phi(1+a)(1-\rho)}{1-\alpha\phi} + \phi\rho\right] > 0$$

While in the absence of aggregate supply shocks the covariance becomes:

[82]This zero covariance property holds so long as wages are more than one period in advance - an assumption which seems justified for quarterly data.

$$(9.16) \quad \mathrm{Cov}(\Delta q_t, \Delta^d y_t) = \left[\frac{1}{(1-\alpha\phi)}\right]\left[\frac{\phi(1-\rho)}{1-\alpha\phi}\right] > 0$$

Real stock returns and real output growth are positively correlated. Furthermore, the covariance is greater in the case when only aggregate supply disturbances are considered:

$$(9.17) \quad \mathrm{Cov}(\Delta q_t, \Delta^s y_t) > \mathrm{Cov}(\Delta q_t, \Delta^d y_t) \quad .$$

From equations (9.10) and (9.11) we can also calculate the covariances between inflation and real output growth. Inflation covaries negatively with real output growth:

$$(9.18) \quad \mathrm{Cov}(\Delta^s p_t, \Delta^s y_t) = -\left[\frac{1+a}{1-\alpha\phi} + (a+\alpha\phi)\left(\frac{1+a}{1-\alpha\phi} - 1\right)\right] < 0$$

$$(9.19) \quad \mathrm{Cov}(\Delta^d p_t, \Delta^d y_t) = -\left[\frac{1}{(1-\alpha\phi)}\right] < 0$$

Furthermore, the covariance is larger (in absolute value) in the case when only aggregate supply disturbances are considered:

$$(9.20) \quad |\mathrm{Cov}(\Delta^s p_t, \Delta^s y_t)| > |\mathrm{Cov}(\Delta^d p_t, \Delta^d y_t)| \quad .$$

In this framework, aggregate supply disturbances reduce consumer prices and increase real output and stock prices, leading to the expected negative relationship between inflation and real stock returns. Positive aggregate demand disturbances increase consumer prices and real output (in the short run). Thus, our simple model is consistent with the proxy hypothesis put forward by Fama

(1981) and Fama and Gibbons (1982) to solve the inflation-stock return puzzle.[83]

From the covariances between inflation, output growth and stock returns obtained from the simple model we expect to find real stock returns to be negatively correlated with inflation movements that are due to aggregate supply innovations. However, real stock returns will not be correlated with inflation due to aggregate demand innovations. Real stock returns are positively correlated with real output growth, and the size of the correlation is expected to be larger when output growth is due to aggregate supply innovations. Inflation and real output growth are negatively correlated whether considering aggregate demand or aggregate supply innovations.

We simulate the above, with a drift term included in equations (9.8) and (9.9) to effect the relations between inflation, real stock returns, and real output growth. To identify the model we assign the following values to the model's parameters: α=0.1, a=0.4, μ_θ=5.0, μ_m=8.0, ϕ=0.6, and ρ=0.96. The value of ρ is taken from Campbell *et al.* (1997) to be 0.96 in annual data.[84]

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[83] The proxy hypothesis suggests that the observed negative correlation between real stock returns and inflation may be due to the conjunction of a positive relationship between aggregate real activity and real stock returns and a negative relationship between real activity and inflation. While the first of these correlations is intuitive, Fama (1981) argues that inflation may negatively covary with real activity effectively to clear the money market. In effect, Fama is assuming a quantity theory of money framework. While many economists might wished to debate the applicability of such a framework in the short run, its long-run applicability would probably achieve greater consensus.

[84] For monthly data, ρ is about 0.997.

A sample of 100 is replicated 200 times. We exploit the generated inflation, real stock return and real output growth series to examine the importance of the aggregate demand and aggregate supply shocks in explaining movements in real stock prices. The correlation coefficients from the simulated data are consistent with equations (9.13)-(9.20). Table 9.1 reports a large negative correlation[85] between real stock returns and inflation. Consistent with the story (and empirical evidence) of Fama (1981), real stock returns are strongly positively correlated with real output growth and inflation is strongly negatively correlated with real output growth. Therefore, the negative inflation-real output growth relationship is proxying for the inflation-real stock return relationship. Moreover, there is no relationship between real stock returns when inflation (or real output growth) is due only to aggregate demand shocks. However, real stock returns are stongly correlated when inflation (negatively correlated) and real output growth (positively correlated) are due to aggregate supply shocks.

The slope coefficients reported in Table 9.2 support the findings from the correlation coefficients. The negative relationship between inflation and real stock returns reflects the fact that real activity is negatively related to inflation and positively related to stock returns. The slope coefficient from regressing real stock returns onto a constant and inflation is negative, and the median coefficient reduces to 0.01 when inflation is due to aggregate demand shocks. Consistent with Fama (1981) and Kaul (1987), the negative relation reduces to -0.09 when

[85]The discussion in the text focuses on the contemporaraneous correlation coefficient.

real output is included as an explanatory variable.

The evidence precented in Chapter 8 indicates the lack of a rigorous empirical investigation of the inflation-stock return puzzle. Previous empirical studies have not been successful in directly considering a fundamental issue that stock returns, inflation and output growth are caused by changes in (real productivity and monetary) policy.[86] This issue is outlined theoretically in the above model. More importantly, we empirically estimate a restricted vector autoregressive representation that is consistent with the above model to effect the results of changes in real and monetary policy on stock returns, inflation and real output growth. In taking this approach we incorporate (and are able to test) many of the issues raise by previous studies (for example, Fisher, 1930; Fama, 1981; Geske and Roll, 1983; Kaul, 1987, 1990; Marshall, 1992) in investigating the inflation-stock return puzzle.

[86] "The stock market is not the "cause" of the increase in output, no more than the increase in output is the cause of the initial stock market change. They are both the results of changes in policy. .....Although .... the change in the stock market and the resulting increase in output will precede the change in policy, they are still caused by it" (Blanchard, 1981, p. 141).

Table 9.1: Cross Correlations from Simulated Data

	x_t	$z_{t+\tau}$	τ = -2	-1	0	1	2
(1)	Δq_t	$\Delta p_{t+\tau}$	.01	.01	-.66	-.04	.35
(2)	Δq_t	$\Delta y_{t+\tau}$	.01	-.03	.70	.03	-.27
(3)	Δp_t	$\Delta y_{t+\tau}$	.54	-.00	-.86	.00	.15
(4)	Δq_t	$\Delta^d p_{t+\tau}$	.00	-.01	.01	-.04	.06
(5)	Δq_t	$\Delta^s p_{t+\tau}$	.00	.01	-.90	-.01	.42
(6)	Δq_t	$\Delta^d y_{t+\tau}$	.01	-.03	.04	.02	-.04
(7)	Δq_t	$\Delta^s y_{t+\tau}$	-.01	-.01	.95	.01	-.32
(8)	$\Delta^d p_t$	$\Delta^d y_{t+\tau}$	.69	.00	-.70	.01	-.01
(9)	$\Delta^s p_t$	$\Delta^s y_{t+\tau}$	.39	-.01	-.99	-.01	.28

Notes: $x_t = \{p_t, y_t, q_t\}$. y_t is the log of real output; p_t is the log of consumer prices; and q_t is the log of real stock prices. $\Delta=(1-L)$ denotes the first difference. The table shows the median (from the 200 simulations) cross correlations between the value of the variable x for period t and the value of the variable z for period $t+\tau$. The sample size is 100.

Table 9.2: The Slope Coefficient from the Regression of x_t onto a Constant and z_t from Simulated Data

	x_t	z_t	Median	5%-ile	95%-ile
(1)	Δq_t	Δp_t	-0.27	-0.31	-0.23
(2)	Δq_t	Δy_t	0.20	0.16	0.23
(3)	Δp_t	Δy_t	-0.58	-0.62	-0.54
(4)	Δq_t	$\Delta^d p_t$	0.01	-0.09	0.12
(5)	Δq_t	$\Delta^s p_t$	-0.49	-0.53	-0.47
(6)	Δq_t	$\Delta^d y_t$	0.02	-0.05	0.08
(7)	Δq_t	$\Delta^s y_t$	0.37	0.35	0.39
(8)	$\Delta^d p_t$	$\Delta^d y_t$	-0.47	-0.48	-0.46
(9)	$\Delta^s p_t$	$\Delta^s y_t$	-0.70	-0.70	-0.68

Notes: See Table 9.1 for definition of variables. The estimated coefficients are the slope coefficients from the regression of x_t onto a constant and z_t. The sample size is 100.

9.2 Empirical Relationships: Real Stock Prices, Real Activity and Inflation

Quarterly data for the United States were obtained from the International Monetary Fund's International Financial Statistics data base for the period 1957i through to 1995ii. The data series of interest are the consumer price index, real gross domestic product (GDP), and the real stock price index (constructed by deflating the stock price index by the consumer price index). All variables are expressed in logarithms.

The cross correlations reported in Table 9.3 show:

1. The change in the logarithm of real stock prices (Δq_t) is negatively correlated with the change in the logarithm of consumer prices (Δp_t) for all leads and lags.
2. Δq_t is positively correlated with the change in the logarithm of real output (Δy_t) for all leads and (weakly) negatively correlated for all lags.
3. Δp_t is negatively correlated with Δy_t for all leads and lags.

These observations are consistent with other studies (for example, Lee, 1989; Marshall, 1992) and confirm the basic relationships between the variables of interest.

The results from estimating basic regressions of stock returns, inflation and real output growth by ordinary least squares are given in Table 9.4. The results are consistent with those of Fama (1981). A strongly significant slope coefficient is found in each regression with the expected sign - real output growth is positively related to real stock returns and negatively related to inflation, and real stock returns is negatively related to inflation.

Table 9.3: Cross Correlations

	x_t	$z_{t+\tau}$	τ = -4	-3	-2	-1	0	1	2	3	4
(1)	Δq_t	$\Delta p_{t+\tau}$	-.09	-.17	-.15	-.25	-.36	-.26	-.19	-.18	-.14
(2)	Δq_t	$\Delta y_{t+\tau}$	-.17	-.17	-.13	-.03	.23	.36	.25	.14	.18
(3)	Δp_t	$\Delta y_{t+\tau}$	.02	-.11	-.16	-.16	-.27	-.37	-.35	-.29	-.32

Notes: $x_t = \{p_t, y_t, q_t\}$. y_t is the natural logarithm of real gross domestic product (GDP); p is the natural logarithm of consumer price index; and q_t is the natural logarithm of the real common stock price index. Δ=(1-L) denotes the first difference. The table shows cross correlations between the value of the variable x for quarter t and the value of the variable z for quarter t+τ. Under the hypothesis that the true correlation coefficient is zero, the critical correlation coefficient value is 0.16 at the 5% level of significance. The sample period is 1957i - 1995ii.

Table 9.4: Basic Regressions

		R^2	s.e.
(1)	$\Delta q_t = \text{dum} - 2.88^* \Delta p_t$ (0.60)	0.17	0.06
	$\Delta q_t = \text{dum} + 1.48^* \Delta y_t$ (0.52)	0.09	0.06
(2)	$\Delta p_t = \text{dum} - 0.23^* \Delta y_t$ (0.07)	0.09	0.01

Notes: Estimation is by OLS. The variables are defined as in Table 9.3. Figures in parentheses denote estimated standard errors. R^2 denotes the coefficient of determination. s.e. is the standard error of the regression. An asterisk denotes significantly different from zero at the 5% level in a two-tailed test. The regressions included quarterly dummies, and are denoted by dum in the table. The sample period is 1957i - 1995ii.

9.3 Isolating Aggregate Demand and Supply Innovations

To identify the aggregate demand and supply innovations to inflation and real output growth we consider the decomposition outlined in Chapter 4, section 4.1. We follow Blanchard and Quah (1989), Bayoumi and Taylor (1995) and Gamber (1996) in using an ADAS framework with a long-run vertical supply curve, and associate aggregate supply shocks with permanent shocks to output and aggregate demand shocks with temporary shocks to output. Interpreting the temporary and permanent innovations as aggregate demand shocks and aggregate supply shocks can be motivated by the simple linear macro model as outlined in the previous section.

Having identified the supply and demand innovations, we can then partition the moving average representation for real GDP growth and inflation to construct counterfactual series, corresponding to the path that would have obtained in the absence of aggregate supply innovations and aggregate demand innovations over the estimation period. By using these counterfactual series we can test the relationship between real stock returns, inflation and real output growth.

As reported in Table 9.5, the change in the logarithm of real GDP, and in the logarithm of the consumer price index are stationary processes. The augmented Dickey-Fuller (ADF) and the Phillips-Perron Z_t unit root tests cannot reject the hypothesis that the series is a realization of a first-difference stationary

I(1) process (Dickey and Fuller, 1979, 1981; Perron, 1988).[87] There is also no evidence of cointegration between real GDP and prices at the 5 percent level of significance. [88]

We follow the estimation procedure as outlined above. A VAR of $[(1-L)y_t \quad (1-L)p_t\ ]'$ was estimated[89] and the residuals were transformed into aggregate demand and aggregate supply disturbances using the transformation matrix A(0) as defined above. The lag depth chosen for the VAR is three and the regression estimates are presented in Table 9.6.[90]

The cumulative impulse response functions illustrating the effect of a one unit standard deviation (supply and demand) shock on the level of real GDP and the price level are shown in Figure 9.1. The cumulative impulse response functions are by assumption consistent with the standard ADAS framework with a long-run vertical supply curve.[91] An aggregate demand shock to inflation is positive, whereas an aggregate supply shock to inflation is negative. By

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[87]This finding is not sensitive to the choice of lag depth.

[88]The augmented Dickey-Fuller test was employed in testing the residuals from the ordinary least squares regression of p_t onto y_t and a constant. The estimated ADF test statistic is -2.01 (the critical value is -3.17, for a 5% significance level).

[89]Seasonal dummies were included in the VAR.

[90]The choice of lag length was tested as follows. First using the Bayes Information Criterion (BIC) the initial lag length was determined. Second using the Ljung-Box Q-statistic we tested for the whiteness of the residuals and the lag depth increased (if necessary) until the residuals were approximately white noise.

[91]Taylor (1996) demonstrates the importance of qualitative restrictions in the context of the Blanchard-Quah decomposition.

assumption, an aggregate demand shock has a zero long-run effect on real output growth. The cumulative impulse response functions are consistent with Bayoumi and Taylor (1995) and Gamber (1996).

Table 9.5: Unit Root Tests

		PP	ADF
Consumer Prices	$\Delta^2 p_t$	-15.02	-14.91
	Δp_t	-3.62	-3.17
	p_t	1.59	0.33
Real GDP	$\Delta^2 y_t$	-19.01	-12.34
	Δy_t	-9.03	-6.65
	y_t	-1.12	-1.16
Real Stock Prices	$\Delta^2 q_t$	-16.42	-12.89
	Δq_t	-9.08	-8.09
	q_t	-1.19	-1.46

Notes: The variables are defined in Table 9.3. Δ^2 denotes the second difference. The unit root tests are the Phillips-Perron Z_t test statistic (PP) and the augmented Dickey-Fuller test statistic (ADF). The ADF and the PP tests the null hypothesis that the series is I(1) (see, Dickey and Fuller, 1979, 1981; Perron, 1988); the lag truncation was set at one. For a 5% significance level the critical Z_t and ADF is -2.89 (see, Fuller, 1976, pp. 371-3). The sample period is 1957i-1995ii.

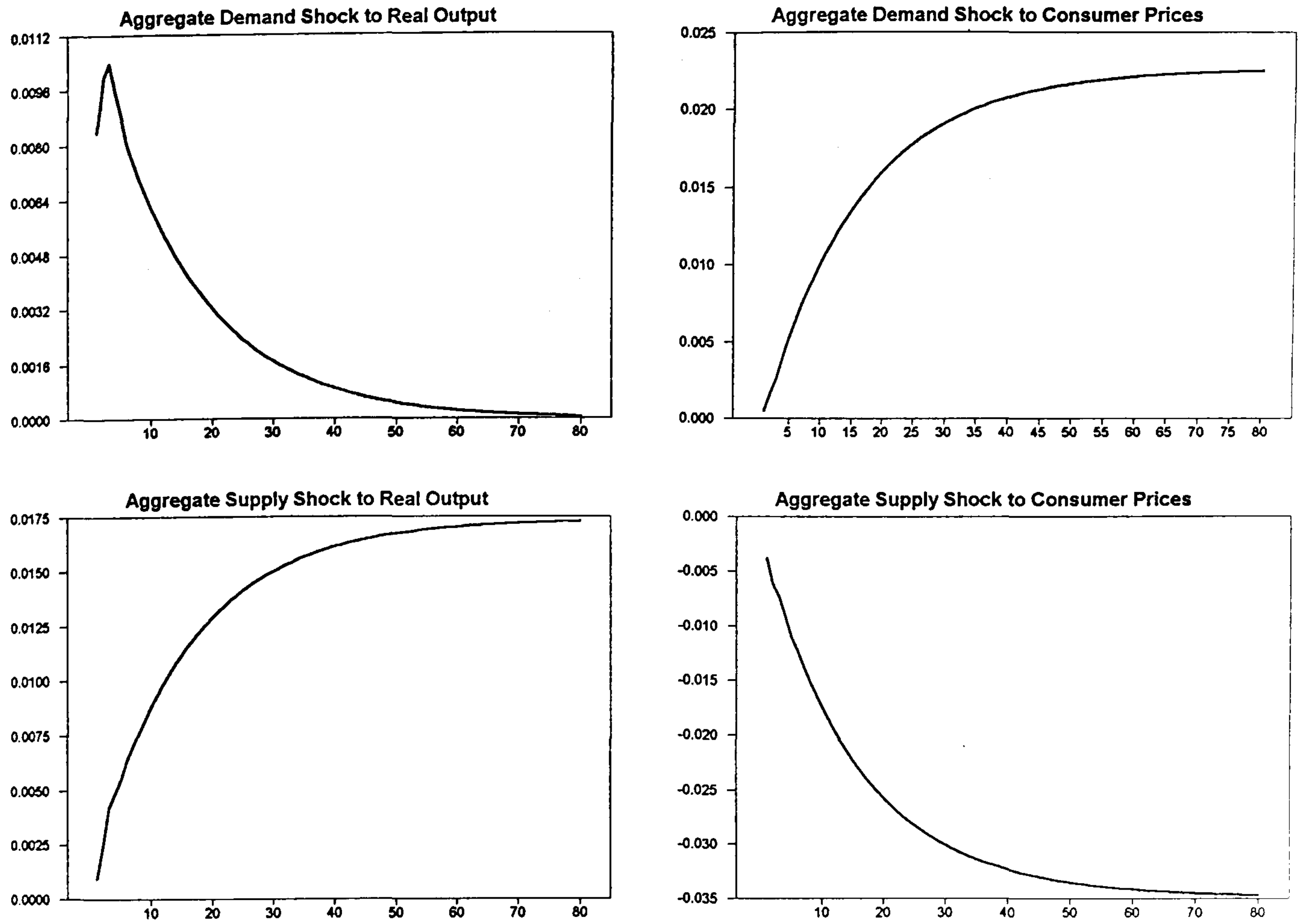
Table 9.6: Regression Coefficients from VAR

Independent Variable	Dependent Variable Δy_t	Dependent Variable Δp_t
Δy_{t-1}	0.2146*	0.0978*
	(0.0830)	(0.0376)
Δy_{t-2}	0.0618	0.0122
	(0.0859)	(0.0389)
Δy_{t-3}	-0.0718	0.0615
	(0.0805)	(0.0365)
Δp_{t-1}	-0.3533*	0.6518*
	(0.1717)	(0.0779)
Δp_{t-2}	-0.1284	-0.0687
	(0.2110)	(0.0957)
Δp_{t-3}	0.1119	0.3938*
	(0.1801)	(0.0817)
Statistics:		
Usable Obs.	150	150
R^2	0.20	0.77
Sum of Squared Error	0.01	0.00
Q(36)	27.65	40.45
	[0.84]	[0.28]

Notes: The variables are defined in Table 9.3. Standard errors are in parentheses below the coefficient estimates. An asterisk denotes significantly different from zero at the 5 percent level. Squared brackets associated with the Ljung-Box Q-statistics denotes significance level for the residuals (for lags 1 through 36). The deterministic parameters are not reported. The sample period is 1957i-1995ii.

Figure 9.1: Cumulative Impulse Response Functions

United States, 1957i - 1995ii



9.4 Empirical Results

We use the estimated aggregate demand (temporary) innovations and the aggregate supply (permanent) innovations to break down the series for real GDP growth and inflation into counterfactual series, corresponding to the path that would have obtained in the absence of aggregate demand innovations in the moving average representation and the path that would have obtained in the absence of aggregate supply innovations. Effectively, this involves using the estimated VAR to recover the moving average representation (given by equation (4.1)), and then calculating a counterfactual series for y_t and p_t by alternately holding the identified aggregate supply and demand shocks constant at zero over the sample period.

The series due entirely to aggregate demand innovations over the sample period (purged of the cumulative effects of aggregate supply innovations over the period) is denoted by a superscript d ($\Delta^d y_t$, $\Delta^d p_t$) while the corresponding series due entirely to aggregate supply innovations over the period is denoted by a superscript s ($\Delta^s y_t$, $\Delta^s p_t$). The counterfactual series along with the actual consumer price series are presented in Figures 9.2 and 9.3.

The results of the basic regressions of real stock returns on the counterfactual series, reported in Table 9.7, are consistent with our simple macro model as outlined in section 9.1 and supportive of the proxy hypothesis. The negative relationship between inflation and real stock returns depends on the source of inflation; i.e. whether it is due to aggregate demand or aggregate supply innovations. Real stock returns and inflation are significantly negatively related in the case when inflation is due to aggregate supply innovations and not in the case when inflation is due to aggregate demand innovations. Also, real stock returns and real output growth are significantly positively related when output is due to aggregate supply innovations and are not related when output is due to aggregate demand innovations.

Consistent with the ADAS framework with a long-run vertical supply curve, real output and inflation are significantly negatively related when both are due to aggregate supply shocks and are not related when both are due to aggregate demand shocks.

Table 9.7 also reports the cross correlations of the counterfactual series and real stock returns. The contemporaneous correlation coefficient between real stock returns and inflation is lower when inflation is due to aggregate demand innovations. Furthermore, the contemporaneous correlation coefficients associated with the counterfactual series are consistent with the proxy hypothesis.

Using decomposed inflation and output series, the results support Fama's proxy hypothesis as an explanation of the stock return-inflation puzzle. These findings are consistent with other studies that use general-equilibrium and partial-equilibrium models (for example, Marshall, 1992; and Danthine and Donaldson, 1986).

Finally, we investigate the robusness of the results to two effects: (i) the periodicity of the data and (ii) the sample time period. These issues are well documented in the inflation-stock return puzzle literature. Boudoukh and Richardson (1993) find a stonger empirical support for the Fisher hypothesis when a longer-horizon is considered. Kaul (1987, 1990) and Graham (1996) provides evidence that the negative relationship is not stable[92] throughout the post-World War II period and is related to the monetary regime adopted by the Federal Reserve. For example, Kaul (1990) finds that during interest rate regimes, periods where monetary policy was (more) counter-cyclical, the (more) strongly negative is the relationship.

The cross correlations and the basic regressions for longer horizons are reported in Table 9.8 and 9.9. Given the sample size and to aviod the inference problems associated with overlapping data we limit the longest horizon to two years. The longer horizon results are similar to the quarterly findings. Moreover, for different horizons, inflation is negatively related to real stock returns is found when inflation is due to aggregate supply (real productivity) innovations and not when inflation is due to aggregate demand (monetary) innovations.

For comparison purposes we consider the subperiods similar to Kaul

[92]Bayoumi and Taylor (1995) find that the forecast error variance decomposition to output and consumer prices changes from the 1970s to the 1980s.

(1990) for the different monetary regimes: 1961i - 1979iii (interest rate regime) and 1979iv - 1995ii (money supply regime). The results from the cross correlations and the basic regressions are presented in Table 9.9. The salient features are similar to those of Kaul (1990). From the basic regressions and the cross correlations, the interest rate regimes period, where monetary policy was (more) counter-cyclical, the relationship between inflation and real stock returns is (more) strongly negative. Furthermore, inflation is negatively related to real stock returns is found when inflation is due to aggregate supply innovations and not when inflation is due to aggregate demand innovations.

Table 9.7: Cross Correlations and Basic Regressions: Counterfactual Series

(A) Cross Correlations

	x_t	$z_{t+\tau}$	τ = -4	-3	-2	-1	0	1	2	3	4
(1)	Δq_t	$\Delta^d p_{t+\tau}$	-.06	-.06	-.15	-.26	-.24	-.14	-.12	-.13	-.08
(2)	Δq_t	$\Delta^s p_{t+\tau}$	-.08	-.15	-.10	-.21	-.38	-.26	-.19	-.23	-.20
(3)	Δq_t	$\Delta^d y_{t+\tau}$	-.17	-.19	-.18	-.09	.16	.25	.19	.14	.07
(4)	Δq_t	$\Delta^s y_{t+\tau}$	.07	.10	.15	.18	.28	.34	.31	.18	.18
(5)	$\Delta^d p_{t+\tau}$	$\Delta^d y_{t+\tau}$	.12	.12	.06	.08	-.08	-.21	-.20	-.16	-.19
(6)	$\Delta^s p_{t+\tau}$	$\Delta^s y_{t+\tau}$	-.52	-.60	-.61	-.67	-.85	-.91	-.76	-.49	-.48

(B) Basic Regressions

		R^2	s.e.
(1)	$\Delta q_t = \text{dum} - \underset{(1.35)}{1.57}\,\Delta^d p_t - \underset{(0.82)}{3.07^*}\,\Delta^s p_t$	0.17	0.06
	$\Delta q_t = \text{dum} + \underset{(0.59)}{0.78}\,\Delta^d y_t + \underset{(1.52)}{4.64^*}\,\Delta^s y_t$	0.12	0.06
(2)	$\Delta^d p_t = \text{dum} - \underset{(0.04)}{0.01}\,\Delta^d y_t$	0.07	0.00
	$\Delta^s p_t = \text{dum} - \underset{(0.08)}{1.72^*}\,\Delta^s y_t$	0.79	0.00

Notes: The variables are defined as in Table 9.3. Panel A of the table shows the cross correlations between the value of the variable x for quarter t and the value of the variable z for quarter t+τ. Under the null hypothesis that the true correlation coefficient is zero, the critical correlation coefficient value is 0.16 at the 5% level of significance. A superscript d denotes the series due entirely to aggregate demand innovations ($\Delta^d y_t$, $\Delta^d p_t$) and a superscript s denotes the series due entirely to aggregate supply innovations ($\Delta^s y_t$, $\Delta^s p_t$). Estimation is by OLS. Figures in parentheses denote estimated standard errors. R^2 denotes the coefficient of determination. s.e. is the standard error of the regression. An asterisk denotes significantly different from zero at the 5% level in a two-tailed test. The regressions included quarterly dummies, and are denoted by dum in the table. The sample period is 1957i - 1995ii.

Table 9.8: Cross Correlations and Basic Regressions: Annual Data

(A) Cross Correlations

	x_t	$z_{t+\tau}$	τ = -4	-3	-2	-1	0	1	2	3	4
(1)	Δq_t	Δp_t	-.06	-.10	.04	-.12	-.50	-.27	-.11	-.20	-.26
(2)	Δq_t	Δy_t	.10	.03	-.02	-.33	.37	.28	-.11	-.07	.01
(3)	Δp_t	Δy_t	-.04	.10	.17	-.04	-.49	-.59	-.29	-.07	.05
(4)	Δq_t	$\Delta^d p_{t+\tau}$	-.00	.01	.05	-.07	-.26	-.05	.02	-.13	-.22
(5)	Δq_t	$\Delta^s p_{t+\tau}$	-.10	-.19	.05	-.15	-.42	-.26	-.10	-.08	-.10
(6)	Δq_t	$\Delta^d y_{t+\tau}$	.10	-.00	-.09	-.39	.34	.13	-.23	-.18	-.05
(7)	Δq_t	$\Delta^s y_{t+\tau}$	.03	.16	.11	.03	.19	.40	.23	.09	.08
(8)	$\Delta^d p_{t+\tau}$	$\Delta^d y_{t+\tau}$	.14	.27	.37	.30	-.30	-.47	-.32	-.20	-.13
(9)	$\Delta^s p_{t+\tau}$	$\Delta^s y_{t+\tau}$	-.10	-.16	-.26	-.47	-.81	-.96	-.63	-.33	-.18

(B) Basic Regressions

		R^2	s.e.
(1)	$\Delta q_t = 0.14 - \underset{(0.77)}{2.62^*}\,\Delta p_t$	0.25	0.14
	$\Delta q_t = -0.05 + \underset{(1.12)}{2.65^*}\,\Delta y_t$	0.14	0.15
	$\Delta p_t = 0.06 - \underset{(0.20)}{0.66^*}\,\Delta y_t$	0.24	0.03
(2)	$\Delta q_t = 0.22 - \underset{(1.27)}{1.63}\,\Delta^d p_t - \underset{(1.12)}{2.77^*}\,\Delta^s p_t$	0.22	0.15
	$\Delta q_t = -0.14 + \underset{(1.30)}{2.63}\,\Delta^d y_t + \underset{(2.57)}{2.57}\,\Delta^s y_t$	0.15	0.15
(3)	$\Delta^d p_t = 0.05 - \underset{(0.16)}{0.30}\,\Delta^d y_t$	0.09	0.00
	$\Delta^s p_t = 0.10 - \underset{(0.23)}{1.80^*}\,\Delta^s y_t$	0.66	0.00

Notes: See notes to Table 9.7. The sample period is 1957 - 1994.

Table 9.9: Cross Correlations and Basic Regressions: 2-Year Horizon

(A) Cross Correlations

	x_t	$z_{t+\tau}$	τ = -4	-3	-2	-1	0	1	2	3	4
(1)	Δq_t	Δp_t	.08	.30	-.16	.01	-.50	-.10	-.21	-.28	-.20
(2)	Δq_t	Δy_t	-.02	-.22	.02	-.15	.34	.01	-.03	-.12	.41
(3)	Δp_t	Δy_t	.08	-.07	.03	.15	-.56	-.44	.03	-.15	-.06
(4)	Δq_t	$\Delta^d p_{t+\tau}$	.02	.20	-.03	.03	-.24	-.07	-.17	-.32	-.42
(5)	Δq_t	$\Delta^s p_{t+\tau}$	.04	.36	-.17	.14	-.58	-.10	-.16	-.13	.07
(6)	Δq_t	$\Delta^d y_{t+\tau}$	.11	-.17	.07	-.20	.18	-.11	-.09	-.22	.50
(7)	Δq_t	$\Delta^s y_{t+\tau}$	-.09	-.33	.06	-.07	.46	.26	.13	.16	-.03
(8)	$\Delta^d p_{t+\tau}$	$\Delta^d y_{t+\tau}$	.09	-.05	.23	.61	-.43	-.31	.09	-.03	-.11
(9)	$\Delta^s p_{t+\tau}$	$\Delta^s y_{t+\tau}$	.27	.26	-.13	-.40	-.97	-.58	-.20	.15	.30

(B) Basic Regressions

	Regression	R^2	s.e.
(1)	$\Delta q_t = 0.23 - \underset{(0.93)}{2.18^*} \Delta p_t$	0.25	0.23
	$\Delta q_t = -0.10 + \underset{(1.55)}{2.21} \Delta y_t$	0.11	0.25
	$\Delta p_t = 0.14 - \underset{(0.32)}{0.85^*} \Delta y_t$	0.31	0.05
(2)	$\Delta q_t = 0.49 - \underset{(1.67)}{1.18} \Delta^d p_t - \underset{(1.43)}{3.54^*} \Delta^s p_t$	0.36	0.23
	$\Delta q_t = -0.42 + \underset{(1.88)}{0.91} \Delta^d y_t + \underset{(3.79)}{6.86} \Delta^s y_t$	0.23	0.26
(3)	$\Delta^d p_t = 0.13 - \underset{(0.25)}{0.44} \Delta^d y_t$	0.18	0.03
	$\Delta^s p_t = 0.23 - \underset{(0.16)}{2.34^*} \Delta^s y_t$	0.94	0.01

Notes: See notes to Table 9.7. The sample period is 1957 - 1993.

Table 9.10: Cross Correlations and Basic Regressions: The Interest Rate Regime, 1961i - 1979iii

(A) Cross Correlations

	x_t	$z_{t+\tau}$	τ = -4	-3	-2	-1	0	1	2	3	4
(1)	Δq_t	Δp_t	.06	-.07	-.10	-.27	-.40	-.35	-.22	-.26	-.14
(2)	Δq_t	Δy_t	-.23	-.07	-.02	.07	.32	.40	.35	.18	.13
(3)	Δp_t	Δy_t	.30	-.02	-.20	-.16	-.30	-.35	-.41	-.30	-.16
(4)	Δq_t	$\Delta^d p_{t+\tau}$	-.17	-.11	-.14	-.28	-.18	-.00	.03	-.02	.09
(5)	Δq_t	$\Delta^s p_{t+\tau}$	.15	.01	-.02	-.21	-.42	-.40	-.28	-.35	-.25
(6)	Δq_t	$\Delta^d y_{t+\tau}$	-.18	-.05	-.05	.01	.25	.29	.24	.08	.08
(7)	Δq_t	$\Delta^s y_{t+\tau}$	-.17	-.09	.05	.20	.35	.49	.44	.34	.22
(8)	$\Delta^d p_{t+\tau}$	$\Delta^d y_{t+\tau}$	.30	.31	.17	.31	.14	-.06	-.08	-.00	-.00
(9)	$\Delta^s p_{t+\tau}$	$\Delta^s y_{t+\tau}$	-.22	-.43	-.49	-.58	-.86	-.86	-.59	-.28	-.22

(B) Basic Regressions

		R^2	s.e.
(1)	$\Delta q_t = \text{dum} - \underset{(1.40)}{3.83^*}\, \Delta p_t$	0.21	0.06
	$\Delta q_t = \text{dum} + \underset{(0.99)}{2.04^*}\, \Delta y_t$	0.15	0.07
	$\Delta p_t = \text{dum} - \underset{(0.10)}{0.22^*}\, \Delta y_t$	0.16	0.01
(2)	$\Delta q_t = \text{dum} - \underset{(3.40)}{0.66}\, \Delta^d p_t - \underset{(1.88)}{5.01^*}\, \Delta^s p_t$	0.23	0.06
	$\Delta q_t = \text{dum} + \underset{(1.12)}{1.38}\, \Delta^d y_t + \underset{(3.56)}{6.37}\, \Delta^s y_t$	0.19	0.07
(3)	$\Delta^d p_t = \text{dum} + \underset{(0.05)}{0.04}\, \Delta^d y_t$	0.16	0.00
	$\Delta^s p_t = \text{dum} - \underset{(0.14)}{1.68^*}\, \Delta^s y_t$	0.80	0.00

Notes: See notes to Table 9.7. The sample period is 1961i - 1979iii.

Table 9.11: Cross Correlations and Basic Regressions: The Money Supply Regime, 1979iv - 1995ii

(A) Cross Correlations

	x_t	$z_{t+\tau}$	τ = -4	-3	-2	-1	0	1	2	3	4
(1)	Δq_t	Δp_t	-.14	-.17	-.07	-.14	-.30	-.10	-.07	-.02	.04
(2)	Δq_t	Δy_t	-.08	-.14	-.17	-.14	.11	.28	.23	.19	.12
(3)	Δp_t	Δy_t	-.08	-.14	-.16	-.10	-.25	-.48	-.39	-.13	-.28
(4)	Δq_t	$\Delta^d p_{t+\tau}$	.02	.06	-.07	-.15	-.15	-.07	-.07	-.06	.04
(5)	Δq_t	$\Delta^s p_{t+\tau}$	-.20	-.23	-.05	-.10	-.28	-.06	-.04	-.01	.03
(6)	Δq_t	$\Delta^d y_{t+\tau}$	-.14	-.23	-.25	-.19	.09	.24	.20	.22	.15
(7)	Δq_t	$\Delta^s y_{t+\tau}$	.21	.17	.20	.11	.14	.14	.13	-.05	-.02
(8)	$\Delta^d p_{t+\tau}$	$\Delta^d y_{t+\tau}$	.13	.14	.07	.02	-.14	-.27	-.33	-.26	-.28
(9)	$\Delta^s p_{t+\tau}$	$\Delta^s y_{t+\tau}$	-.38	-.39	-.41	-.53	-.76	-.83	-.59	-.20	-.21

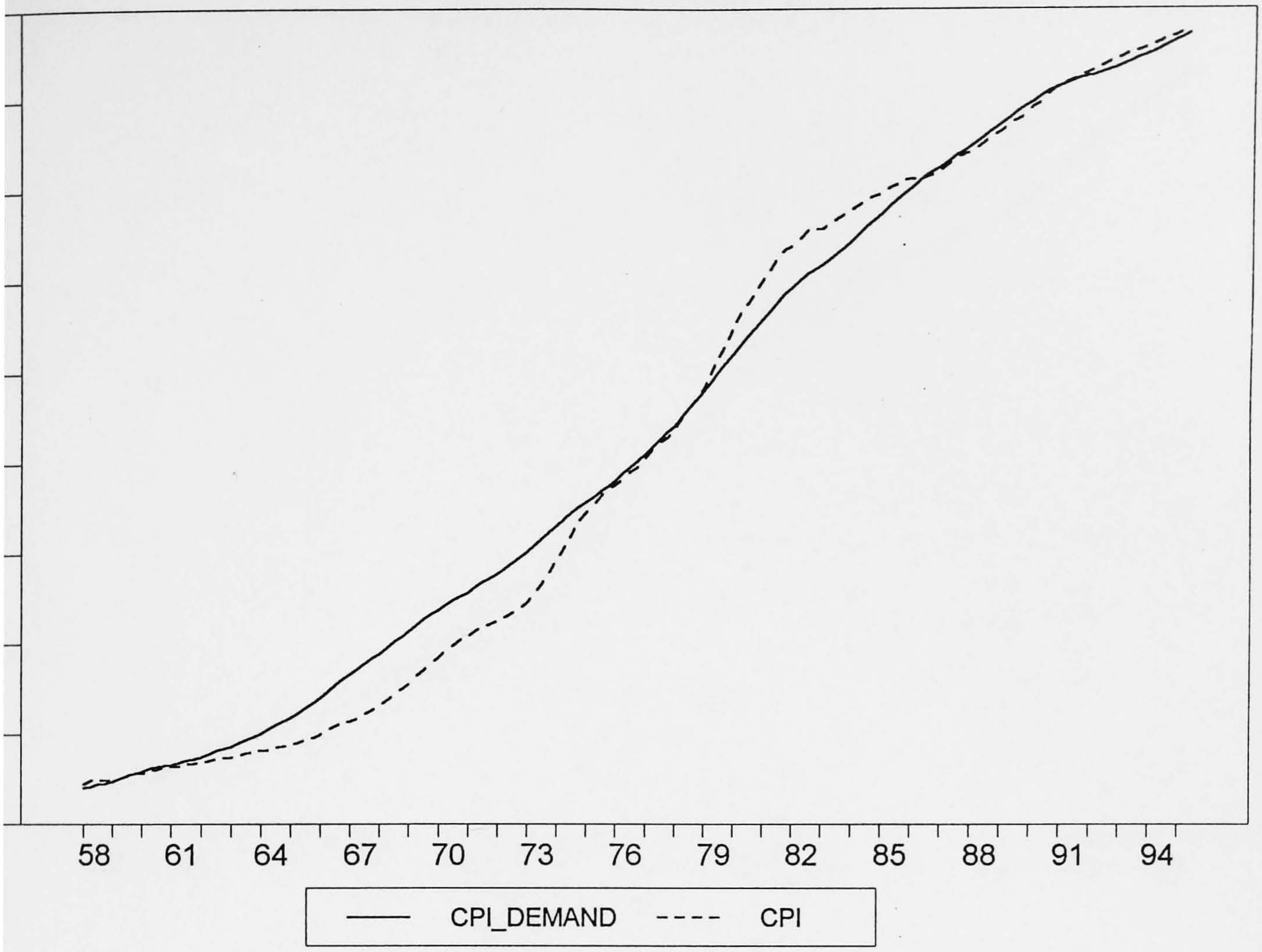
(B) Basic Regressions

		R^2	s.e.
(1)	$\Delta q_t = \text{dum} - \underset{(1.01)}{2.51^*}\, \Delta p_t$	0.14	0.06
	$\Delta q_t = \text{dum} + \underset{(0.92)}{0.91}\, \Delta y_t$	0.06	0.06
	$\Delta p_t = \text{dum} - \underset{(0.11)}{0.21}\, \Delta y_t$	0.06	0.01
(2)	$\Delta q_t = \text{dum} - \underset{(1.82)}{1.68}\, \Delta^d p_t - \underset{(1.36)}{3.02^*}\, \Delta^s p_t$	0.14	0.06
	$\Delta q_t = \text{dum} + \underset{(1.00)}{0.75}\, \Delta^d y_t + \underset{(2.81)}{2.04}\, \Delta^s y_t$	0.06	0.06
(3)	$\Delta^d p_t = \text{dum} - \underset{(0.07)}{0.07}\, \Delta^d y_t$	0.05	0.00
	$\Delta^s p_t = \text{dum} - \underset{(0.16)}{1.56^*}\, \Delta^s y_t$	0.62	0.00

Notes: See notes to Table 9.7. The sample period is 1979iv - 1995ii.

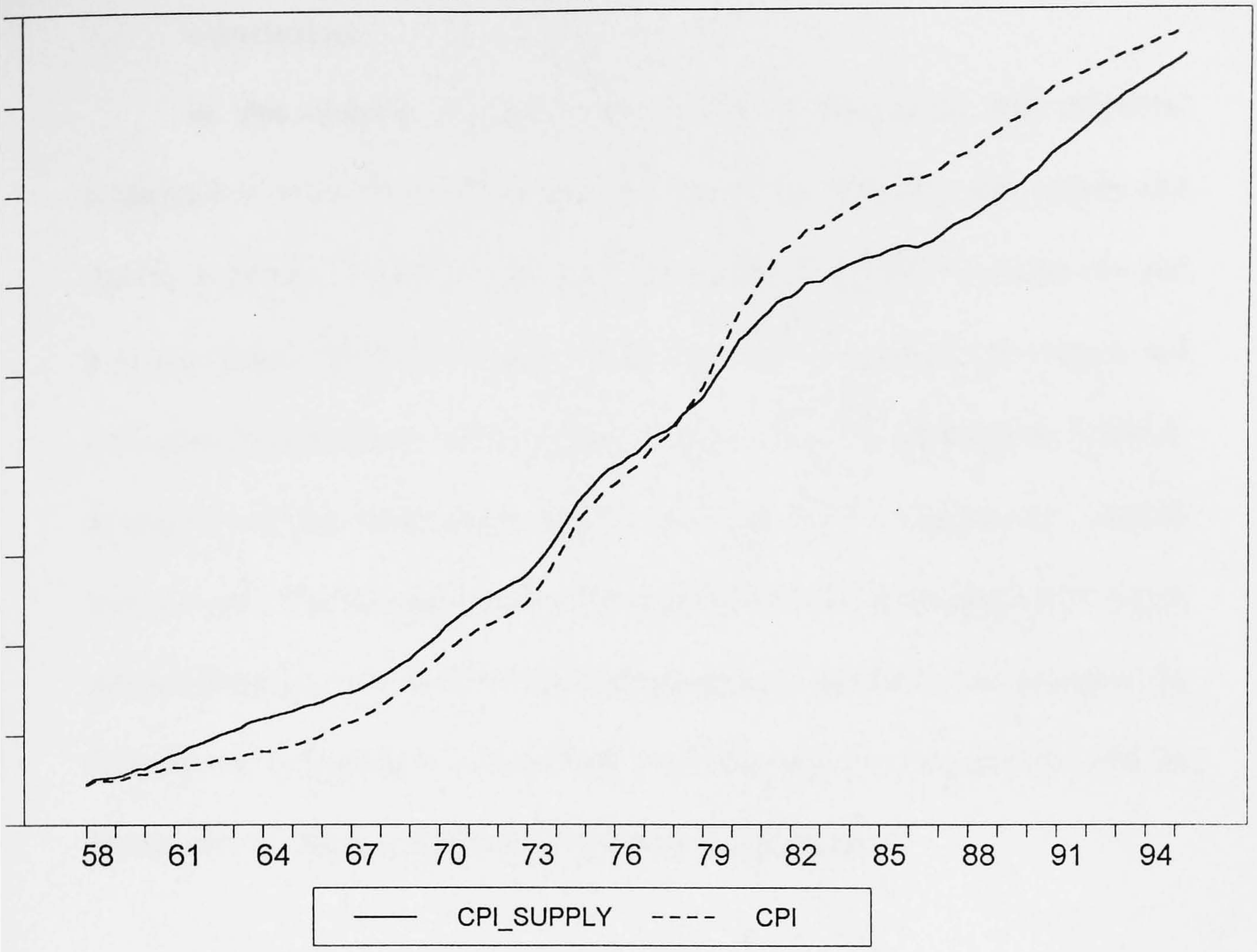
e 9.2.Consumer Price Index Due to Aggregate Demand Shocks

United States, 1957i - 1995ii



ıre 9.3:Consumer Price Index Due to Aggregate Supply Shocks

United States, 1957i - 1995ii



9.5 Conclusion

In this chapter, we have carried out a theoretical and empirical investigation of the observed correlation between US inflation, real activity and real stock returns. Using a multivariate innovation decomposition method - and a simple macro model to identify the innovations - we purged the output and consumer price series of, alternately, movements over the sample period due to aggregate supply innovations and movements due to aggregate demand innovations. The counterfactual series were then used to investigate the stock return-inflation puzzle in the context of inflation and output series generated by fluctuations in aggregate supply (real economic activity fluctuations) and by fluctuations in aggregate demand (monetary fluctuations).

The negative correlation between inflation and real stock returns were found to depend on the source of inflation; i.e. whether it is due to aggregate demand or aggregate supply innovations. This finding supports Fama's proxy hypothesis as an explanation of the stock return-inflation puzzle. Moreover, the relationship between real stock returns and inflation due to aggregate demand innovations is insignificantly different from zero - supporting the Fisher hypothesis. Also, as suggested by the proxy hypothesis, real stock returns are strongly negatively related with the portion of inflation due to aggregate supply innovations. Real stock returns and real output growth are significantly positively related when output is due to aggregate supply innovations and not aggregate demand innovations.

Chapter 10

THE PRESENT VALUE MODEL OF STOCK PRICES AND NON-LINEARITY

10.1 Introduction

In this chapter we examine some theoretical issues and tests of the present value model of stock prices. An implication of the present value model of stock prices is that stock prices and dividends should be cointegrated. It is this hypothesis that we empirically investigate in the following chapter. If we cannot reject the null hypothesis of no cointegration then the present value model may be either misspecified in its depiction of the relationship between stock prices and fundamentals, or there may be other problems such as the presence of speculative bubbles,[93] or the discount rate may be nonstationary time-varying.

There exists a number of competing theories that explain the deviation of the market and fundamental values (represented by expected value of future discounted dividends) , including noise traders (DeLong *et al.*, 1990), fads (Shiller, 1984) and speculative bubbles (Blanchard and Watson, 1982). These theories suggest that stock prices move away from their fundamental value for periods of time. As discussed in Chapter 2, for common stocks, there are limits

[93]The apparent presence of bubbles may simply reflect left-out variables (Hamilton and Whiteman, 1985; Obstfeld and Rogoff, 1986). Furthermore, evidence of cointegration between stock prices and dividends does not necessarily imply that no rational bubble exist (Evans, 1991). This contrast to the finding by Diba and Grossman (1988) and Koop (1991).

to arbitrage and prices deviate from fundamentals in a highly persistent way that reflects a random walk process (see, for example, Schaefer, 1982; Summers, 1986; Shleifer and Summers, 1990; Shleifer and Vishny, 1997). Furthermore, "[r]isk-averse speculators will only be willing to take limited positions when they perceive valuation errors. Hence errors will not be eliminated unless they are widely noticed" (Summers, 1986, p. 599). Therefore, although stock prices may reflect their fundamentals in the long run, they may deviate substantially from their fundamentals for long periods of time (De Long *et al.*, 1990).

The evidence of cointegration between real stock prices and dividends, expressed as either levels or logs, is at best mixed (for example, Campbell and Shiller, 1987; Diba and Grossman, 1988; Koop, 1991; Mills, 1993b; MacDonald, 1994; Lee, 1995; MacDonald and Power, 1995; Timmermann, 1995; Han, 1996; Yuhn, 1996). The majority of studies find weak support for the cointegrating relationship. However, a common feature of these studies is that the short-run dynamics of the cointegration relationship are linear. A number of recent studies suggest that stock prices may in fact be non-linearly cointegrated (Diba and Grossman, 1988; Hardouvelis, 1990; Koop, 1991; Yuhn, 1996)[94] or a linear cointegrating representation may be misspecified due to left-out variables (MacDonald and Power, 1995).

The possibility that the relationship between real stock prices and

[94]These studies do not formally model the non-linearity element of stock prices.

dividends is non-linear is consistent with the limits to arbitrage hypothesis (see, Shleifer and Summers, 1990; Shleifer and Vishny, 1997) and the mixed empirical cointegrating findings.[95]

The potential non-linear relationship between stock prices and dividends is highlighted by a number a recent papers (for example, Kalay, 1982; Miller and Scholes, 1982; Karpoff and Walkling, 1988, 1990; Boyd and Jagannathan, 1994). Boyd and Jagannathan (1994) examine the price behaviour around ex-dividend dates and found a non-linear relation between percentage price fall and dividend yield. This finding is a result of transactions costs and heterogeneous traders with different transaction costs and/or tax treatments.

Modelling the short-run dynamics as a non-linear process may capture features of the stock market that are left out of the basic present value model, for example, limits to arbitrage (Schaefer, 1982; Summers, 1986; DeLong *et al.*, 1990; Shleifer and Summers, 1990), margin requirements (Hardouvelis, 1990), and transaction costs and taxation effects (Kalay, 1982; Miller and Scholes, 1982; Karpoff and Walkling, 1988, 1990; Boyd and Jagannathan, 1994). It is this feature that we investigate in this essay.

We exploit the recent developments in cointegration and non-linearity to

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[95]A number of other studies have reported evidence of non-linearity in modelling exchange rates and fundamentals (see, for example, Balke and Fomby, 1997; Michael, Nobay and Peel, 1997; Michael, Peel and Taylor, 1997; Taylor and Peel, 1997).

investigate the deviation of the real stock price from the linear long-run equilibrium real stock price suggested by the present value model. Moreover, in Chapter 11, we test whether there is evidence of non-linear error correction towards the present value model and then parsimoniously model the non-linearity in US real stock prices. The evidence reveals that the error correction term should be modelled as a non-linear process.

10.2 The Present Value Model of Stock Prices

The present value model of stock prices represents stock prices in terms of the expected present discounted value of all future dividends and has proven to be very popular in finance, in particular in modelling market efficiency. The advantage of the present value model is that it is a simple dynamic stochastic model. Following previous studies we specify the present value model of stock prices in both level and log forms (Campbell and Shiller, 1987, 1988a,b; Han, 1996; Campbell *et al.*, 1997).

Present Value Model of Stock Prices

The present value model of stock prices as presented by Campbell and Shiller (1987) and others relates real stock prices (Q_t) to their expected future real dividends (D_t) discounted using a constant discount rate.[96]

$$(10.1) \quad Q_t = E_t \sum_{j=1}^{\infty} \rho^j D_{t+j}$$

where $\rho = (1+R)^{-1}$ is a constant discount factor, and R is the (constant)expected stock return. E_t is the conditional expectations operator, conditional on the full information set which includes Q_t and D_t . Furthermore, we treat conditional expectations as equivalent to linear projections on information.

[96]Timmermann (1995) analyses cointegration tests in the presence of a time-varying discount rate in the present value model. The cointegration results are fairly robust to a time-varying discount rate.

This representation of the present value model shows that Q_t is a linear function of the present value of the expected future D_t and assumes away the possibility that there are so-called rational bubbles in stock prices. If real dividends follow a linear process with a unit root then real stock prices also follow a linear process with a unit root. Therefore, since (10.1) relates two unit-root processes for Q_t and D_t, we can rewrite the present value model in terms a linear combination of two nonstationary variables:

$$(10.2) \qquad Q_t - \left(\frac{1}{R}\right) D_t = \left(\frac{1}{R}\right) E_t\left[\sum_{j=0}^{\infty} \rho^j \Delta D_{t+1+j}\right]$$

The difference between the real stock price and (1/R) times the real dividend is equal to the expectation of the discounted value of future changes in real dividends. If changes in real dividends are stationary, then a linear combination of real stock prices and dividends must be stationary, that is the 'spread', $S_t = Q_t - \beta D_t$, is stationary, where β is the cointegrating vector and given as $\rho/(1-\rho)$. Thus the present value model supports the hypothesis that real stock prices and dividends are cointegrated, assuming they are both first-difference stationary.[97] Furthermore, the cointegrating relationship implies a real discount rate R equal to the reciprocal of the cointegrating vector, $1/\beta$.

[97] If Q_t and D_t are both I(1) processes and are cointegrated, then the spread, $S_t = Q_t - \beta D_t$, and the change in dividends, ΔD_t , must together form a jointly covariance stationary process. A weak implication of the present value model is that S_t must Granger-cause ΔD_t unless S_t is itself an exact linear function of current and lagged ΔD_t (Campbell and Shiller, 1987).

A number of studies have estimated this cointegrating relationship with mixed results (see, for example, Campbell and Shiller, 1987; Koop, 1991; Mills, 1993b, Han, 1996). Applying univariate cointegration tests, Campbell and Shiller (1987) find weak evidence of cointegration between stock prices and dividends. The low power of univariate cointegration tests is a potential explanation for the weak evidence of cointegration (see, for example, Koop, 1991; Mills, 1993b; Han, 1996). They estimate two theoretical spreads, one using the estimated cointegrating vector and the other using the sample mean return. The spread estimated using the cointegrating vector rejects the null hypothesis of no cointegration while the latter estimated spread accepts the null. Therefore, the latter finding suggests that the spread between stock prices and dividends moves too much and that deviations from the present value model are quite persistent.

In a similar study to that of Campbell and Shiller (1987), Mills (1993b,c) examines UK data and finds that univariate cointegration tests (Engle and Granger, 1987) are unable to reject the null of no cointegration, whereas multivariate tests (Johansen, 1988, 1991; Johansen and Juselius, 1990) reject the null of no cointegration. The implied discount rates are similar to those of Campbell and Shiller (1987).

The present value model implies a number of highly nonlinear cross-equation restrictions similar to those of rational expectations models, as identified by Hansen and Sargent (1981). Campbell and Shiller (1987) shows that, given β and ρ, the restrictions can be simplified so that its restrictions are linear. Define the excess return on stocks over a constant mean, multiplied by the stock price, as the asset return $\xi_t \equiv Q_t - (1/\rho)[Q_{t-1} - \beta(1-\rho)D_{t-1}]$. If the present value model holds then $\xi_t = S_t - (1/\rho)S_{t-1} + \beta\Delta D_t$, and is unpredictable given lagged ΔD_t and S_t. A simple Wald test statistic for a regression of ξ_t on lagged ΔD_t and S_t is a test of the cross-equation restrictions and is therefore a strong test of the present value model.

A feature of the present value model of stock prices is that Q_t and D_t are not measured contemporaneously. As pointed out by Campbell and Shiller (1987) and West (1988a) this might lead to a spurious rejection of the present value model if in fact D_t is known only at the start of period t+1. Campbell and Shiller (1987) suggest that the spread term S_t should be constructed as $S_t \equiv Q_t - \beta D_{t-1}$. For the empirical work, in the following chapter, we use this definition of S_t in the tests of the cross-equation restrictions.

Stock prices and dividends appear to grow exponentially over time rather than linearly (Campbell *et al.*, 1997). Therefore, a loglinear present value model may be more appropriate than a linear model, even one that allows for a unit root (Kleidon, 1986). For this reason we consider a loglinear representation of the present value model

Loglinear Present Value Model of Stock Prices

There are a number of alternative ways to write the loglinear version of the present value model (see Campbell and Shiller, 1988a,b; Campbell, 1991;

Campbell *et al.*, 1997; Cuthbertson, Hayes and Nitzsche, 1997). For our purpose we assume that expected real stock returns are constant and express the present value relation as presented by Campbell and Shiller (1988a):[98]

$$(10.3) \qquad q_t - d_t = \sum_{j=0}^{\infty} \rho^j E_t \Delta d_{t+1+j} + k^*$$

where q_t and d_t are the log of real stock prices and real dividends, respectively. The discount rate R is a constant equal to the average dividend-price ratio, where $\rho=(1+R)^{-1}$, and k^* is a constant. The loglinear present value model (10.3) shows that when q_t and d_t are first-difference stationary, I(1) processes, they are also cointegrated with a cointegrating vector $(1, -1)'$, that is, the dividend-price ratio, $\delta_t=d_t-q_t$, is stationary. Therefore, unlike the level version of the present value model, the stationary linear combination of the log of real stock prices and dividends involves no unknown parameters. This feature makes the loglinear version of the present value model of stock prices particularly appealing in empirical work.[99] A test of the cross-equations restrictions of the loglinear present value model, with constant expected excess returns, is a Wald test statistic for a regression of ξ_t on lagged δ_t and Δd_t, with $\xi_t \equiv k + \rho q_t + (1-\rho)d_t - q_{t-1} = k - \rho\delta_t + \delta_{t-1} + \Delta d_t$, and $k = -\log(\rho) - (1-\rho)\log(1/\rho - 1)$ (see, Campbell and Shiller, 1988b). In order to avoid the problem that q_t and d_t are not measured

[98]See Chapter 3, Appendix 3.1, for the derivation of equation (10.3).

[99]The present value model as described by (10.3) can easily be extended to include a time-varying discount rate without affecting the implication of the cointegration tests (see Campbell *et al.*, 1997).

contemporaneously, we modify the cross-restrictions tests by constructing the log dividend-price ratio as $\delta_t = d_{t-1} - q_t$.

Han (1996) examines two alternative cointegration tests of the present value of real stock prices for - the same data set as Campbell and Shiller (1987) - annual US stock prices, 1871-1986. The evidence tends to accept the hypothesis of no cointegration between real stock prices and real dividends, either in levels or logs.

There are a number of alternative approaches in testing the present value model of stock prices, including volatility tests (LeRoy and Porter, 1981; Shiller, 1981, 1989, 1990; Mankiw *et al.*, 1985; Scott, 1985; West, 1988a,b; Bulkley and Tonks, 1989, 1992; Gilles and LeRoy, 1991; Cochrane, 1991b,c, 1992).[100] These studies found that fluctuations in stock prices are too large to result from changes in the expected present discounted value of dividends. That is stock prices exhibit excess volatility. West (1988a,b) suggests that the excess volatility is due either to rational bubbles (Blanchard and Watson, 1982) or nearly rational fads (Summers, 1986).[101] More recently, Froot and Obstfeld (1991) find that intrinsic bubbles [102] provide a more plausible empirical account of deviations from the

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[100]The earlier volatility tests (e.g., LeRoy and Porter, 1981; Shiller, 1981) have been criticized by subsequent studies (Flavin, 1983; Kleidon, 1986; Marsh and Merton, 1986) because of small sample bias.

[101]Campbell and Shiller (1987) find that, because S_t and ΔD_t are stationary, a rational bubble does not appear to be present in US data. Similar evidence is reported by Mills (1993b) for UK data. However, such tests have low power in detecting bubbles.

[102]Intrinsic bubbles are rational bubbles that depend exclusively on aggregate dividends.

present value model than traditional rational bubbles.

The cointegration test of the present value model also generates a test of excess volatility. If stock prices and dividends are I(1) processes and cointegrated then the implied discount rate can be used to calculate a theoretical spread. A comparison of the variance of the theoretical spread with the variance of the actual spread is a test of excess volatility. Campbell and Shiller (1987) and Mills (1993b,c) reject the null hypothesis of no excess volatility. If the variance inequality implied by the volatility tests is violated - stock prices are excessively volatile - then the difference between the present value of actual future dividends and the stock price is forecastable (Campbell and Shiller, 1988a,b; Diba and Grossman, 1988; Evans, 1991a). Therefore, the evidence of excess volatility is consistent with the finding of multi-period predictability of stock returns as presented in Chapter 2 (also see, Campbell and Shiller, 1988a, Cochrane, 1992; Mills, 1993b,c).

10.3 Modelling Non-Linear Adjustment in the Present Value Model

Linear models are too restrictive to capture adequately asymmetries that may exist in the present value model. For example, introducing transaction costs into the present value model may also introduce an asymmetry into the long-run adjustment. Stock prices may follow a unit root process when prices are close to their long-run equilibrium and only mean-revert when prices are substantially away from their long-run equilibrium (i.e., their fundamental value), while the speed of adjustment towards equilibrium varies directly with the extent of the deviation from the long-run equilibrium. A similar asymmetry would be associated with the limits to arbitrage hypothesis.

A parsimonious parametric non-linear model which has been shown to approximate well a broad range of non-linearity (Granger and Teräsvirta, 1993) is the exponential autoregressive (EAR) model, original proposed by Haggan and Ozaki (1981) and recently reconsidered by Priestley (1988), Granger and Teräsvirta (1993), and Teräsvirta (1994). Another popular class of non-linear models that captures asymmetries is the threshold autoregressive (TAR) model (Tong, 1983, 1990; Tong and Lim, 1980; Tsay, 1989).[103] For an extensive discussion of TAR models see Tong (1990). The TAR model is appropriate if there is a threshold level of the absolute deviation from equilibrium beyond which

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[103] A number of recent studies have found that persistence varies over the business cycle and, in particular, recessionary shocks are less persistent than are expansionary shocks. Non-linear model can be applied to capture this asymmetry (see, for example, Granger and Teräsvirta, 1993; Pesaran and Potter, 1994; Potter, 1995). TAR models have also been applied to financial data (Cao and Tsay, 1992).

the spread (i.e., the deviation from the long-run equilibrium) becomes mean-reverting, whilst exhibiting unit root behaviour elsewhere.

Teräsvirta (1994) combined the EAR and the TAR models into a single family of models called smooth transition autoregressive (STAR) models. The STAR model has the advantage of capturing the asymmetries associated with the TAR models but as a modelling procedure it is less restricted (see Chan and Tong, 1986; Luukkonen, Saikkonen and Teräsvirta, 1988a,b; Granger and Teräsvirta, 1993; Teräsvirta, 1994).[104]

For STAR modelling of the long-run adjustment in the present value representation, the adjustment takes place in every period but the speed of adjustment varies with the extent of the deviation from equilibrium. Where the long-run equilibrium is given by the cointegration relation between real stock prices and real dividends and, therefore, the adjustment represents the short-run dynamic behaviour, i.e, the error correction. However, for STAR models, regime changes occur gradually (smoothly) rather than abruptly, as they do in TAR models. A smooth, rather than a discreet regime change is likely to be more realistic and appropriate when dealing with aggregated processes (Granger and Teräsvirta, 1993; Teräsvirta, 1994).

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[104]The TAR modelling procedure assumes at the outset that the only alternative to the linear autoregressive model is the TAR model. Moreover, problems with the TAR model arise from the discontinuity at each of the thresholds which complicates the testing of linearity. Also, it is not clear how inference about the estimated thresholds should be conducted (Tsay, 1989; Tong, 1990; Granger and Teräsvirta, 1993; Balke and Fomby, 1997).

We assume that if the adjustment process to the long-run equilibrium is not linear, then it is a STAR model. Define the equilibrium deviation as the residual in the cointegrating regression of real stock prices onto real dividends.

$$(10.4) \quad y_t = q_t - \beta d_t$$

where q_t are real stock prices, d_t are real dividends, and β is the cointegrating vector. If variables are expressed in logs β is expected to be equal to 1. Whereas, if the variables are expressed in levels, $\beta = 1/R$ is expected.[105] The adjustment variable y_t is by definition assumed to be a stationary process and modelled as an exponential smooth transition autoregressive model of order p (ESTAR(p) model):

$$(10.5) \quad y_t = \kappa + \sum_{i=1}^{p} \pi_i y_{t-i} + [\kappa^* + \sum_{i=1}^{p} \pi_i^* y_{t-i}][1 - \exp\{-\gamma^*[y_{t-d} - c^*]^2\}] + u_t$$

where y_t is assumed stationary and ergodic, $u_t \sim$ iid $N(0, \sigma^2)$, and $\gamma^* > 0$.[106] The transition function $F[y_{t-d}] = 1 - \exp\{-\gamma^*[y_{t-d} - c^*]^2\}$ is U-shaped with the (smoothness) parameter γ determining the speed of the transition process between

[105]The present value model defines the adjustment in the present value model as a stationary variable. If the present value model is expressed in levels, the 'spread' represents this stationary adjustment variable. Expressed in logs, the price-dividend ratio is the adjustment variable.

[106]The ESTAR model can be viewed as a generalisation of the regular EAR model of Haggan and Ozaki (1981) with $k^*=c^*=0$, or as a generalisation of a special case of a double-threshold TAR model (Teräsvirta, 1994).

extreme regimes.[107] The middle ground can have different dynamics to the outer ground. Moreover, the middle regime corresponds to F = 0, $y_{t-d} = c^*$, and (10.5) becomes a linear AR(p) model:

$$(10.6) \quad y_t = \kappa + \sum_{i=1}^{p} \pi_i y_{t-i} + u_t$$

The outer regime corresponds to the limit, $\mathrm{Lim}_{y_{t-d} \to \pm\infty} F = 1$ and (10.5) becomes a different AR(p) model:

$$(10.7) \quad y_t = (\kappa + \kappa^*) + \sum_{i=1}^{p} (\pi_i + \pi_i^*) y_{t-i} + u_t$$

For our purpose, it is also informative to reparameterize the ESTAR model in (10.5) as follows:

$$(10.8) \quad \Delta y_t = \kappa + \lambda y_{t-1} + \sum_{i=1}^{p-1} \phi_i \Delta y_{t-i}$$
$$+ [\kappa^* + \lambda^* y_{t-1} + \sum_{i=1}^{p-1} \phi_i^* \Delta y_{t-i}][1 - \exp\{-\gamma^* [y_{t-d} - c^*]^2\}] + u_t$$

In this form the crucial parameters are λ and λ^*. For global stability we require $(\lambda + \lambda^*) < 0$. However, if it is the case that the larger the deviation from the long-run equilibrium, the stronger is the tendency to move back to fundamental equilibrium, then we must have $\lambda^* < 0$ and $(\lambda + \lambda^*) < 0$, while $\lambda \geq 0$ is possible. That

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[107]In practice, when estimating (10.5) it is useful to standardize the exponent of the transition function F by dividing it by $\hat{\sigma}^2(y)$, the sample variance of y_t and choose a starting value for (standardized) γ^* equal 1.

is, for small deviations y_t may follow a unit root or even explosive behaviour, but for large deviations the process is mean reverting.

Another model of interest is the logistic smooth transition autoregressive model of order p (LSTAR(p) model), in which the transition function F is modelled as a logistic function of y_{t-d}. That is, $F[y_{t-d}] = (1+\exp\{-\gamma[y_{t-d}-c]\})^{-1} - 0.5$, with $\gamma>0$. The LSTAR model differs radically from the ESTAR model in that, the parameters in the LSTAR model change monotonically with the transition function, while the change is nonmonotonic in the ESTAR model. In fact, the logistic function yields asymmetric adjustment towards equilibrium[108] according to the sign of $[y_{t-d} - c]$. This type of asymmetry we view as unattractive in the present context since *a priori*, one might expect stock price adjustment to be symmetric around the long-run equilibrium - the parameters change symmetrically about c^* with y_{t-d}. The test procedures, described in the following section, are designed to test for the possibility of either ESTAR or LSTAR adjustment.

[108]The LSTAR model contains as a special case the single-threshold TAR model (Granger and Teräsvirta, 1993; Teräsvirta, 1994)

10.4 Linearity Testing and Model Selection

The specification of STAR models consists of three steps: (i) Specification of a linear AR model. (ii) Testing linearity and, if rejected, detecting the delay parameter d. (iii) Choosing between ESTAR and LSTAR models. It is these three steps that are outlined in the following section. In the first step, the order of the AR may be selected by considering the partial autocorrelation function (PACF) of y_t or an information criteria, for example, the Akaike Information Criterion (AIC), [109]

The second stage of non-linear modelling is testing for linearity against, in our case, STAR. If linearity is rejected, the next issues will be the specification of the model (selecting the appropriate STAR family), estimating its parameters, and evaluating the estimated model. As the transition function in (10.5) implies that F=0 when $\gamma=0$, the linearity hypothesis may be expressed as $H_0{:}\gamma=0$ and the alternative $H_1{:}\gamma>0$, that of non-linearity. If the null cannot be rejected, then the model is a linear AR(p) model, as defined by (10.6) and the parameter vector $\underline{\phi}=(c^*, \kappa^*, \pi_1^*, ..., \pi_p^*)$ can take any value. To overcome this problem, Teräsvirta (1994) takes the approach of Davis (1977), where a Lagrange Multiplier (LM) test statistic, LM($\underline{\phi}$), is first derived assuming the unidentified parameters in $\underline{\phi}$ fixed, and then the value of the statistic corresponding to $sup_{\underline{\phi}}$ LM($\underline{\phi}$) is

[109]Tsay (1989) suggests that the PACF approach is more appropriate than some information criteria, e.g., the Akaike Information Criterion (AIC), because (i) the information criteria could be misleading when the true process is nonlinear, and (ii) unlike the information criteria selection processes, the PACF imposes no penalty on a higher order AR, when it may be the case that high-order AR models could provide reasonable approximations to a nonlinear model.

selected.[110] In the case of STAR models, the resulting statistic follows a central χ^2 distribution under H_0. The solution involves approximating the transition function by a Taylor series expansion around the equilibrium and reparameterizing in such a way that the identification problem disappears (see Luukkonen, Saikkonen and Teräsvirta, 1988b; Saikkonen and Luukkonen, 1988). Following these studies, Teräsvirta (1994) derives LM-type tests of linearity against LSTAR or ESTAR models and also suggests a decision rule for choosing between LSTAR and ESTAR.[111] In practice, the F-test form of the LM test is preferred to the corresponding χ^2-test because it improves size and power properties in finite samples , especially for large p (Harvey, 1990). If the delay parameter d is fixed, the linearity test against STAR consists of testing

$$(10.9) \quad H_{0L}: \beta_{2i} = \beta_{3i} = \beta_{4i}, \qquad i = 1, \cdots, p$$

against the alternative that H_{0L} is not valid in the artificial regression:

$$(10.10) \quad y_t = \beta_{00} + \sum_{i=1}^{p} [\beta_{1i} y_{t-i} + \beta_{2i} y_{t-i} y_{t-d} + \beta_{3i} y_{t-i} y_{t-d}^2 + \beta_{4i} y_{t-i} y_{t-d}^3] + \varepsilon_t$$

and estimation is by ordinary least squares.

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[110] Equivalently the value of the statistic corresponding to $\inf_{\phi}$ P[LM(ϕ)] is selected, where P[·] denotes the P-value or marginal significance level.

[111] This modelling technique has been applied to several macroeconomic time series in Teräsvirta and Anderson (1992) and Granger and Teräsvirta (1993).

In order to specify the delay parameter d, the linearity test is carried out for a set of values d = 1,2,....,D. If linearity is rejected for more than one value of d, then d is determined as the delay parameter ($\hat{d}$) which minimises the P-value of the linearity test. Linearity is most strongly rejected when d = $\hat{d}$. For a discussion of this selection rule see Tsay (1989) and Granger and Teräsvirta (1993).

If the null hypothesis H_{0L} in (10.9), using and F-test (F_L), is rejected and the appropriate delay parameter $\hat{d}$ is determined, $F_L(\hat{d}) = sup_d\, F_L(d)$, d = 1,...., D, the third step is to choose between the family of STAR models: ESTAR and LSTAR models. Teräsvirta (1994) proposes a sequence of nested tests within (10.10). The following sequence of hypotheses are tested in turn:

$$(10.11a) \quad H_{04}: \beta_{4i} = 0, \qquad i = 1,\cdots,p$$

$$(10.11b) \quad H_{03}: \beta_{3i} = 0 \mid \beta_{4i} = 0, \qquad i = 1,\cdots,p$$

$$(10.11c) \quad H_{02}: \beta_{2i} = 0 \mid \beta_{3i} = \beta_{4i} = 0, \qquad i = 1,\cdots,p$$

Choosing between LSTAR and ESTAR models using the hypotheses in (10.11) is essentially a test of selecting the appropriate restrictions on the third-order Taylor expansion (10.10). For ESTAR models, the restrictions $\beta_{4i} = 0$, for all i, whereas usually $\beta_{4i} \neq 0$ if the model is LSTAR. Whereas, usually $\beta_{3i} \neq 0$ if the model is ESTAR and $\beta_{3i} = 0$ if the model is an LSTAR model. More specifically Granger and Teräsvirta (1993) show that if the model is an ESTAR, and if $\kappa^* = c^* = 0$ and $\beta_{2i} = 0$, the restrictions $\beta_{4i} = 0$ holds for all i, whereas for LSTAR models the restrictions holds only if $\pi_1^* = ... = \pi_p^* = 0$. Similarly, the restrictions $\beta_{3i} = 0$, for all i, hold if $\kappa^* = c^* = 0$, whereas for ESTAR models they hold only if

$\pi_1^*=.....=\pi_p^*=0$.[112]

The F-test is used to calculate the test statistics of (8.11a-c), and are denoted by F_4, F_3, and F_2, respectively. The selection rule is as follows. If the test of H_{03} (given by (8.11b)) has the smallest P-value, choose an ESTAR model, otherwise select a LSTAR model.[113]

Teräsvirta (1994) found that the decision rule tended to select correctly LSTAR models. This is also the case for the ESTAR model when the observations are symmetrically distributed about c^* (i.e., when $c^*=0$ and $\kappa^*=0$). However, when the true model is an ESTAR and also the observations are asymmetrically distributed around c^*, that is, most of the observations either lie above or below c^*, the ESTAR and LSTAR models are close substitutes for each other and the decision rule tends to select LSTAR as the appropriate model. Teräsvirta (1994) suggests that if the P-values for F_4 and F_3 or for F_3 and F_2 have similar values, then the choice of which STAR model should be left until both models are estimated and then choose the model based on results of the post-estimation model evaluation.

[112]If the true model is ESTAR with $c^*=0$ and/or $k^*\neq 0$ (10.11a) may sometimes be rejected because of neglected higher (than the third) order terms of the Taylor expansion, at least if the significance level of the test is high enough and/or the sample size is large. This means that the LSTAR is selected too frequently. However, a rejection of (10.11a) is more likely and more often stronger for an LSTAR model than for an ESTAR one (Teräsvirta, 1994).

[113]Accepting H_{03} after rejecting H_{02} indicates that the true model is an ESTAR (Teräsvirta, 1994).

To check whether the H_{02} was wrongly rejected, Michael, Peel and Taylor (1997) suggest adding to the tests (10.11a-c) another F-test (F_0) which tests the following hypothesis:

$$(10.11d) \quad H_{00}: \beta_{2i} = \beta_{4i} = 0, \qquad i = 1, \cdots, p$$

If the model is non-linear and, as in our case, is expected to be an ESTAR one, Teräsvirta (1994) proposes a modified sequence of hypotheses testing in determining whether the model is nonlinear and in selecting the delay lag.[114] If the delay parameter d is fixed, a more powerful test of linearity against ESTAR consists of testing

$$(10.12) \quad H^{*}_{0L}: \beta_{2i} = \beta_{3i} = 0, \qquad i = 1, \cdots, p$$

using an F-test (F^{*}_{L}), against the alternative that H^{*}_{0L} is not valid in the auxiliary regression:

$$(10.13) \quad y_t = \beta_{00} + \sum_{i=1}^{p} [\beta_{1i} y_{t-i} + \beta_{2i} y_{t-i} y_{t-d} + \beta_{3i} y_{t-i} y^2_{t-d}] + \varepsilon_t$$

and estimation is by ordinary least squares. If the null hypothesis is rejected for some d, we can further simplify the ESTAR model. Given that we are interested in examining the deviations from the present value model, represented by y_t, we expect the ESTAR model to satisfy $\kappa^* = c^* = 0$ and therefore, $\beta_{2i} = 0$. Michael,

[114]This procedure follows from work by Saikkonen and Luukkonen (1988).

Peel and Taylor. (1997) propose a further F-test (F_k) test:

$$(10.14) \qquad H_{0k}\colon \beta_{2i} = 0\,, \qquad i = 1, \cdots, p$$

If H_{ok} is not rejected, a more powerful test than (10.12) of linearity against ESTAR consists of testing

$$(10.15) \qquad H_{0L}^{**}\colon \beta_{3i} = 0 \mid \beta_{2i} = 0\,, \qquad i = 1, \cdots, p$$

using an F-test (F_L^{**}), against the alternative that H_{0L}^{**} is not valid in (10.13).

If theory suggests that the (potential) non-linearity is represented by an ESTAR model, then the decision rule is to use the test H_{0L}^{*} (H_{0L}^{**}) as a test of linearity, for some delay parameter $\hat{d}$, where $F_L^{*}(\hat{d}) = sup\, F_L^{*}(d)$, d = 1,...., D. For completeness and, moreover, as a check that ESTAR is appropriate it is useful to test H_{0L} and (10.11a-c). If linearity is rejected in favour of an ESTAR(p) model, the last stage is to estimate (10.5) by non-linear least squares, which provides estimators that are consistent and asymptotically normal.[115] Investigating more parsimonious models reveals the variables which can be omitted from the final model specification. Also, the model should be checked to ensure that the parameters are reasonable. In our case, we would expect that mean reversion occurs with large deviations from the long-run equilibrium (identified by the present value model) and small deviations may follow a unit root or be explosive.

[115]Klimko and Nelson (1978) present the conditions for the estimators to be consistent and asymptotically normal. Tong (1990) showed that if the STAR model is stationary and ergodic, with $u_t \sim$ iid $N(0,\sigma^2)$, then the conditions of Klimko and Nelson (1978) hold.

This would show up in (10.8) as $\lambda^{*}<0$ and $\lambda^{*}+\lambda<0$, with $\lambda \geq 0$.

Finally, model evaluation of the resulting ESTAR(p) model should include an check of the residuals. Recent studies have suggested a batch of diagnostic tests for an evaluation of ESTAR models (see, for example, Granger and Teräsvirta, 1993; Teräsvirta, 1994, 1995; Eitrheim and Teräsvirta, 1996).

Chapter 11

TESTING THE PRESENT VALUE MODEL AND NON-LINEARITY: EVIDENCE FROM U.S. STOCK PRICES

11.1 Introduction

In this chapter we test the present value model for stock prices and investigate the time series properties of the cointegrating relationship implied by the present value model of stock prices. According to the present value model, real stock prices and dividends are cointegrated. Previous empirical findings tend to be mixed. Moreover, the emprical results from the cross-equation restrictions tests reject the present value model of stock prices (Campbell and Shiller, 1987). A noticeable feature of previous studies is that in modelling the present value model the cointegrating relationship is linear. Motivated by a number of recent studies (Summers, 1986; Campbell and Shiller, 1987, 1988a,b; DeLong *et al.*, 1990; Hardouvelis, 1990; Shleifer and Summers, 1990; Boyd and Jagannathan, 1994; Shleifer and Vishny, 1997) we explore the hypothesis that the equilibrium error is non-linear and is approximated well by an ESTAR model.

Using quarterly data on real stock prices and dividends for the US we first, test the present value model. Three tests are considered; the cross-equation restrictions, the Granger-causality relationship, and the cointegration between real stock prices and dividends. Second, we test for evidence of non-linear error correction towards the present value model. Third, we parsimoniously model the non-linearity in US real stock prices.

The Granger-causality and cointegrating results support the present value model. However, a stronger test of the present value model, testing cross-restrictions of the model is strongly rejected. Moreover, the evidence reveals that the error correction term should be modelled as a non-linear process. Monte Carlo evidence provides supporting evidence.

11.2 Data and Summary Statistics

The data set used to examine non-linearity adjustment in the present value model is obtained from the Center for Research in Securities Prices (CRSP). The stock price and dividend data is from the CRSP Indices files and consumer prices is from the SBBI series (Ibbotson and Associates). For empirical estimation, we use quarterly data for the period 1926i to 1995iv.[116]

To derive the nominal stock price index and nominal dividend series, we use the quarterly value-weighted nominal returns with dividends ($R1_t$) and the value-weighted nominal returns without dividends ($R2_t$). The nominal stock price index is calculated as $NQ_t = (1+R2_t)Q_{t-1}$, with the price in 1995iv set equal to one, and the nominal dividend series is given by $ND_t = (R1_t - R2_t)Q_{t-1}$.

The consumer price index is taken from the SBBI files (Ibbotson and Associates) of the CRSP. The real stock price (Q_t) and dividend (D_t) series are generated by deflating the nominal series by the consumer price index. The log of real stock prices is denoted by q_t and the log dividends by d_t.

As evident in Figure 11.1, the quarterly dividend series reveals some

[116]We initially considered monthly data, however, the dividend series reveals a high degree of seasonality which is likely to obscure the unit root tests of dividend, price-dividend ratio and spread series. Testing for the presence of unit root required a long lag depth in the augmented Dickey-Fuller (ADF) test to ensure white noise and, moreover, the Phillips-Perron (PP) test could not accept the null hypothesis of a unit root. Thus there is only weak evidence that the monthly dividend series is an I(1) process. Similarly, there is only weak support for the hypothesis that the price-dividend ratio and the spread are stationary.

degree of seasonality. This may obscure the unit root tests of dividends and spread series. For this reason, the real dividend series (both levels and logs) were deseasonalized by regressing the series against seasonal dummies, and using the deseasonalized dummies for empirical estimation. Table 11.1 reports some summary statistics on the variable series of interest. The sample autocorrelations of the price and dividend series reveal some degree of persistence in each series as they tend to die of slowly. The first-order autocorrelation values close to one suggest that the series are non-stationary.

Preliminary unit root testing, reported in Table 11.2, confirms that the price and dividend series are generally I(1) processes.[117] The unit root tests are the augmented Dickey-Fuller (ADF) and the Phillips-Perron (PP) for the null hypothesis that the series in question is I(1) (see Dickey and Fuller, 1979, 1981; Perron, 1988). The lag length was chosen as four as this ensured the absence of serial correlation in the residual of the ADF regressions. The test results support the null hypothesis that the stock price and dividend series are I(1) and that the log price-dividend ratio series are I(0).

---

[117]The sequential procedure employed in testing for unit roots follows from Dickey and Pantula (1987) in order to ensure that only one unit root is present in the series. The results from these unit root test support the finding that the stock price and dividend series are I(1) and the log price-dividend ratio series is I(0).

Table 11.1: Summary Statistics

	Mean	Std Dev	Skew	Kurt	Autocorrelation, ρ(k)					
					ρ(1)	ρ(2)	ρ(3)	ρ(4)	ρ(5)	ρ(6)
D_t			-0.126	-0.667*	.90*	.87*	.86*	.88*	.83*	.80*
Q_t			0.432*	-0.879*	.97*	.93*	.90*	.88*	.85*	.83*
ΔD_t	0.000	0.007	-0.613*	3.903*	-.43*	-.02	-.18*	.35*	-.07	-.08
ΔQ_t	0.036	0.444	-0.923*	2.913*	.07	-.02	.03	-.07	.01	-.04
d_t			-0.666*	-0.534	.90*	.89*	.85*	.89*	.81*	.79*
q_t			-0.229	-1.059*	.97*	.94*	.91*	.88*	.86*	.83*
$(q_t - d_t)$	1.474	0.291	-0.458*	-0.133	.77*	.74*	.63*	.65*	.53*	.49*
Δd_t	0.003	0.218	-0.358*	2.895*	-.64*	.38*	-.56*	.76*	-.53*	.33*
Δq_t	0.006	0.112	0.316*	8.439*	-.05	.01	.16	-.18*	.01	.01
$\Delta(q_t - d_t)$	0.004	0.192	0.332*	1.686*	-.42*	.16	-.29*	.33*	-.19*	.11

Notes: The sample period is 1926i-1995iv. ρ(k)=autocorrelation between x_t and x_{t-k}. D_t is the real dividend series, Q_t is the real stock price series, Δ=(1-L) denotes the first difference, and d_t and q_t are the log of the dividend series and stock price series, respectively. An asterisk denotes significantly different from zero at the 5 percent level. Skew and Kurt denotes standard skewness and kurtosis statistics as reported in Kendall and Stuart (1958) and estimated by RATS.

Table 11.2: Results of Unit Root Tests:

	ADF	PP
<u>Levels:</u>		
Q_t	-0.3265	-0.4599
D_t	-1.2309	-2.9070*
ΔQ_t	-7.2115*	-15.4984*
ΔD_t	-7.6426*	-31.8345*
<u>Logs:</u>		
q_t	-1.2940	-1.5194
d_t	-1.6912	-3.0659*
$(q_t - d_t)$	-2.9739*	-5.1347*
Δq_t	-7.6676*	-17.5041*
Δd_t	-6.5609*	-42.5540*
$\Delta(q_t - d_t)$	-8.0994*	-27.6722*

Notes: See Table 11.1 for definition of the variables. The unit root test are the Augmented Dickey-Fuller (ADF) and the Phillips-Perron Z_t (PP) test statistics without time trend and with constant, for the null hypothesis that the series is I(1) (Dickey and Fuller, 1979, 1981; Perron, 1988). The lag truncation of four was chosen.. The critical ADF and PP is -2.57 at the 10%, -2.88,at the 5%, and -3.46 at the 1% level of significance (Fuller, 1976, p. 373). An asterisk rejected at the 5% level of significance of the null hypothesis that the series is a unit root. The sample period is 1926i-1995iv.

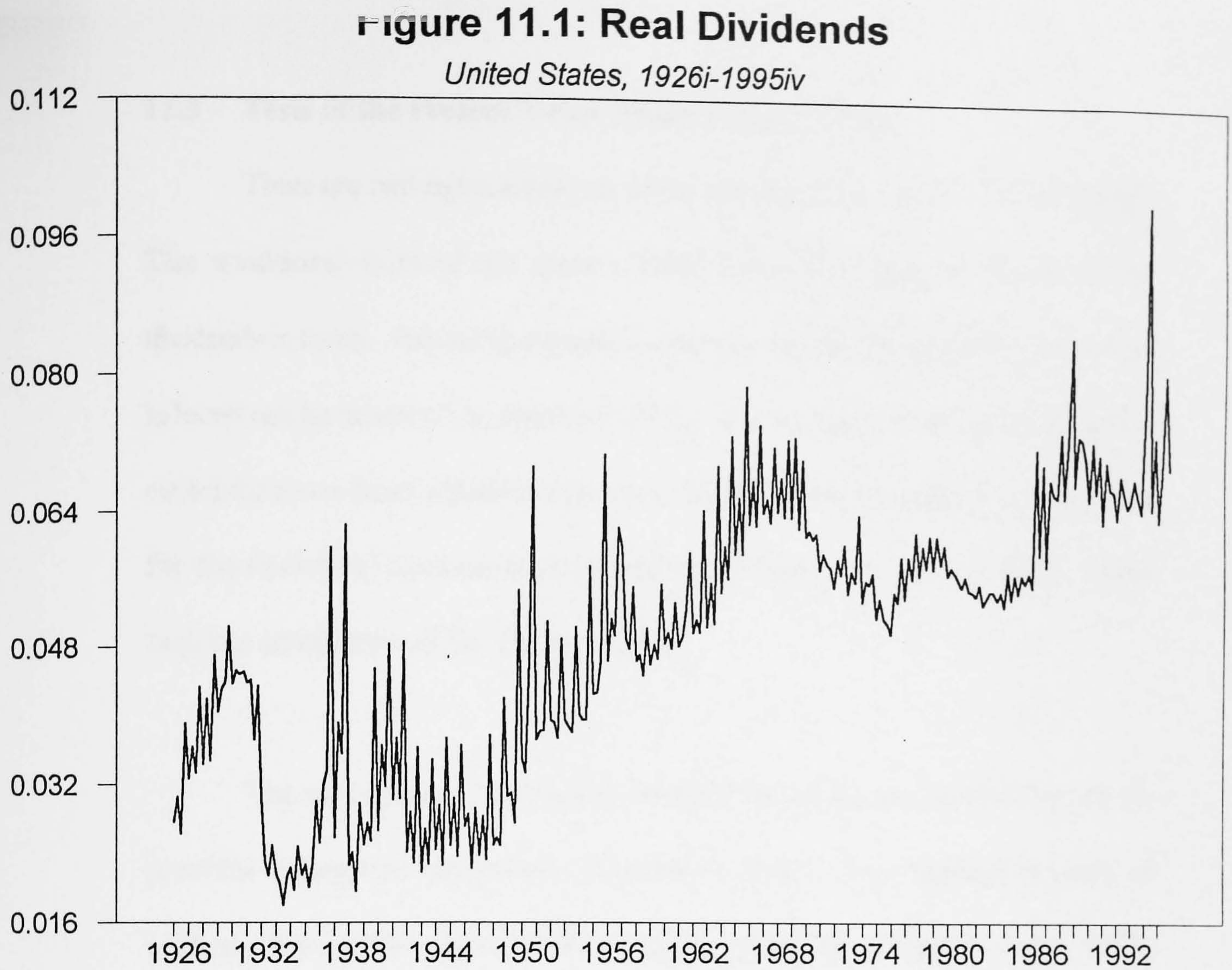


Figure 11.1: Real Dividends
United States, 1926i-1995iv
0.112
0.096
0.080
0.064
0.048
0.032
0.016
1926 1932 1938 1944 1950 1956 1962 1968 1974 1980 1986 1992

11.3 Tests of the Present Value Model of Stock Prices

There are two representations of the present value model of stock prices. The traditional form of the present value model expresses stock prices and dividends in levels. Assuming a constant discount rate R, the present value model in levels can be described by equation (10.2). We are interested in evaluating this model for a non-linear adjustment process. To effect this we estimate a time series for the deviations from the present value equilibrium $y_t = Q_t - (1/R)D_t$, which requires an estimate of the discount rate R.

The cointegration relationship between Q_t and D_t, as described by (10.4), provides a long-run equilibrium estimate of (1/R). Two alternative testS of cointegration are the augmented Dickey-Fuller (ADF) (Engle and Granger, 1987) and the Johansen maximum likelihood (Johansen, 1988, 1991; Johansen and Juselius, 1990). As discussed in Chapter 10, previous studies suggest that the univariate cointegration tests (e.g., ADF) tend accept the null of no cointegration, whereas multivariate tests (e.g., Johansen ML) reject the null of no cointegration. Balke and Fomby (1997) provide Monte Carlo evidence that suggests employing the Johansen ML estimation technique, when adjustment towards equilibrium is non-linear, does not lead to misleading results in terms of significant loss of power or size distortion. However, for comparison purposes we examine both tests to derive the long-run linear equilibrium and the adjustment series y_t.

The real stock price and dividend series are both first-difference stationary, I(1) processes, and a linear ordinary least squares (OLS) regression of real stock prices onto real dividends and a constant for the 1926i-1995iv period is given by

$$
\begin{array}{lll}
Q_t & = 4.9844 & + 133.8047\, D_t \\
 & (0.0773) & (4.9734) \\
 & [64.5022] & [26.9043]
\end{array}
$$

$$
\begin{array}{llll}
DW & = 0.6315 & s & = 1.2930 \\
R^2 & = 0.7225 & ADF(4) & = -2.8648
\end{array}
$$

The implied annualised discount rate of 3.02% is similar to other studies (see, for example, Campbell and Shiller, 1987; Mills, 1993b). Moreover, the ADF cointegration test, with lag length set at four, rejects the null hypothesis of no cointegration only at the 10 percent level (see Table 11.3). The calculated ADF of −2.86, with the marginal critical values given by −2.88 at the 5% level and −2.57 at the 10% level.

In Table 11.3 we also report the Trace and maximum eigenvalue statistics for the test of cointegration using the Johansen maximum likelihood estimation technique and setting the lag length equal to four. On the basis of these statistics, we may reject the null hypothesis real stock prices and dividends are not cointegrated. Therefore, real stock prices and dividends are cointegrated with a long-run equilibrium given by $Q_t = 164.351\, D_t$ and an implied annualised discount rate equal to 2.46%. Given the evidence presented in Table 11.3, we can conclude that real stock prices and dividends are cointegrated (at least at the 10% level of significance) and therefore exists a long-run equilibrium relationship between real stock prices and dividends. Furthermore, the present value model of stock prices describes this long-run equilibrium.

Campbell and Shiller (1987) identify a strong test of the present value model of stock prices. The test is a simple Wald test of the cross-equation restrictions of the model - if the model holds then asset returns ξ_t are unpredictable - the the test statistic is for a regression of ξ_t on a lagged information set, given by lagged ΔD_t and S_t. The ADF and PP unit root test suggest that S_t and ξ_t are stationary, for the implied annualised discount rate of 3.02 percent, ρ=0.9926 (β=133.8047), or the discount rate of 2.46 percent, ρ=0.9940 (β=164.351).[118] We test the cross-equation restrictions of the present value model by regressing ξ_t on a constant and lagged ΔD_t and S_t for both discount rates. The Akaike information criterion (AIC) and the Bayes information criterion (BIC) selected a five-lag representation for both cases.

Table 11.4 reports summary statistics of the estimated Wald cross-restrictions tests of the present value model. White's (1984) heteroscedasticity-consistent covariance matrix estimator is used in constructing standard errors and test statistics. In both cases the degree of explanatory power is high and greater than 70 percent. The Wald tests that asset returns are unpredictable, that is, the lagged ΔD_t and S_t are jointly zero, are strongly rejected at less than the 0.0001 percent level. Thus for quarterly US stock prices, and similar to other studies, the present value model is statistically rejected at all conventional significance levels (see, for example, Campbell and Shiller, 1987). A weak test of the present value model, that the price-dividend spread Granger-cause dividend, is supported by the

[118]The estimate of ρ is consistent with previous studies (see, for example, Campbell *et al.*, 1997; Cuthbertson *et al.*, 1997).

data. In the next section, the properties of the adjustment to the long-run equilibrium described by the present value model are explored. We consider the equilibrium errors associated with the OLS and the Johansen ML estimation techniques.

The alternative representation of the present value model is a loglinear form and given by (10.3). The loglinear present value model shows that when the log of real stock prices and the log of real dividends are first-difference stationary they are cointegrated with a cointegrating vector $(1, -1)'$, that is, the log price-dividend ratio is stationary. Therefore, the long-run equilibrium relationship described by the present value model is given by $q_t = d_t$, or equivalently, q_t and d_t are cointegrating with a cointegrating vector $(1, -1)'$. The results from the two tests of cointegration are reported in Table 11.3. The OLS regression of log real stock prices on log real dividends and a constant is given by

$$\begin{aligned} q_t &= \underset{\substack{(0.0165)\\ [89.4894]}}{1.4742} + \underset{\substack{(0.0458)\\ [27.5605]}}{1.2623}\, d_t \end{aligned}$$

$$\begin{array}{llll} DW & = 0.6799 & s & = 0.2757 \\ R^2 & = 0.7321 & ADF(4) & = -3.7286 \end{array}$$

The ADF test, with a lag length set at four, rejects the null hypothesis of no cointegration. If we impose a unity slope coefficient and test the stationarity of the log price-dividend ratio, the ADF test statistic is -2.97 and the Phllips-Perron (PP) test statistic is -5.13 (see Table 11.2). On the basis of these unit root statistics we accept the hypothesis that the log price-dividend ratio is stationary.

Further evidence is provided by the Johansen ML estimation technique which strongly rejects the null hypothesis no cointegration, with the long-run equilibrium given by $q_t = 1.431\ d_t$. Moreover, the likelihood ratio statistic that $q_t = d_t$, asymptotically distributed as $\chi^2(1)$ under the null hypothesis, is 5.58 with a marginal significance level of 2%. The cointegration results suggest that the long-run equilibrium of the log real stock prices is described by $q_t = d_t$, with the adjustment to this equilibrium given by the log price-dividend ratio.

Table 11.4, part b, repeats the cross-equation restrictions tests of the loglinear present value model. The results are similar to the traditional present value model and previous studies (Campbell and Shiller, 1988b). The Wald tests even more strongly reject the hypothesis that the asset returns are unpredictable. Whereas, the Granger-causality tests indicates a weak acceptance for the present value model.

These cointegration and Granger-causality results generally support the present value model of stock prices either expressed in logs or level. However, the cross-restrictions tests strongly reject the present value model. A potential explanation could be that the present model in linear form does not adequately capture key features of the stock market - for example, transaction costs and limits on arbitrage - which could be modelled more appropriately as non-linear. Taking the present value model of stock prices as defining the long-run equilibrium relationship between real stock prices and real dividends we next examine potential non-linearity in the adjustment to the this long-run equilibrium.

Table 11.3: Results from Cointegration Tests

$Q_t = 4.9844 + 133.8047\,D_t$	DW = 0.63
(0.0773) (4.9734)	$R^2 = 0.72$
[64.5022] [26.9043]	ADF = -2.86
Implied Annual Discount Rate = 3.02%	

Johansen Maximum Likelihood Estimation

$Q_t = 164.351\,D_t$

Implied Annual Discount Rate = 2.46%

H_0	λ-Max	10% Critical Values	Trace	10% Critical Values
r=0	13.86	10.60	13.96	13.31
r≤1	0.10	2.71	0.10	2.71

(b) Logs

$q_t = 1.4742 + 1.2623\,d_t$	DW = 0.68
(0.0164) (0.0458)	$R^2 = 0.73$
[89.4894] [27.5605]	ADF = -3.73

Johansen Maximum Likelihood Estimation

$q_t = 1.431\,d_t$

LR Test for β=1: $\chi2(1) = 5.58$

P-value = 0.02

H_0	λ-Max	10% Critical Values	Trace	10% Critical Values
r=0	17.37	10.60	18.69	13.31
r≤1	1.31	2.71	1.31	2.71

Note: r denotes the number of cointegrating vectors. The lag truncation of 4 was chosen using the Ljung-Box Q-statistic to ensure whiteness of the VAR (and ADF regression) residuals. The critical values of the Johansen cointegration tests are those reported in CATS in RATS. The sample period is 1926i-1995iv.

Table 11.4: Tests of the Present Value Model

β=133.8047 (3.02% discount rate)
AIC/BIC selects a lag length of five
Test of present value model: $\chi^2(10)$: 508.12; P-value < 0.0001%
$R^2 = 0.734$; DW = 2.031; SSE = 195.233

Granger Tests
ΔD_t equation $R^2 = 0.441$; S_t Granger-causes ΔD_t at 0.056%
S_t equation $R^2 = 0.890$; ΔD_t Granger-causes S_t at <0.0001%

β=164.351 (2.46% discount rate)
AIC/BIC selects a lag length of five
Test of present value model: $\chi^2(10)$: 517.46; P-value < 0.0001%
$R^2 = 0.756$; DW = 2.033; SSE = 262.570

Granger Tests
ΔD_t equation $R^2 = 0.448$; S_t Granger-causes ΔD_t at 0.005%
S_t equation $R^2 = 0.903$; ΔD_t Granger-causes S_t at <0.0001%

(b) Logs

ρ=0.9926 (3.02% discount rate)
AIC/BIC selects a lag length of five
Test of present value model: $\chi^2(10)$: 756.548; P-value < 0.0001%
$R^2 = 0.738$; DW = 1.996; SSE = 6.725

ρ=0.9940 (2.46% discount rate)
AIC/BIC selects a lag length of five
Test of present value model: $\chi^2(10)$: 756.404; P-value < 0.0001%
$R^2 = 0.738$; DW = 1.996; SSE = 6.734

Granger Tests
Δd_t equation $R^2 = 0.561$; δ_t Granger-causes Δd_t at 0.001%
δ_t equation $R^2 = 0.875$; Δd_t Granger-causes δ_t at <0.0001%

11.4 Results from Linearity Tests

We are interested in testing linearity of three long-run equilibrium adjustment processes. The first two are derived from the equilibrium error associated with the cointegration of real stock prices and real dividends, and the third is the log stock price-dividend ratio. Balke and Fomby (1997) show that standard tests (for example, the ADF) for detecting cointegration are also capable of testing cointegration in the presence of non-linear adjustment.

The three long-run equilibrium adjustments are given by,

(i) $y_{1t} = Q_t - 4.9844 - 133.8047\,D_t$

(ii) $y_{2t} = Q_t - 164.351D_t$

(iii) $y_{3t} = q_t - d_t$

We test for linearity, by specifying an autoregression AR(p) that represents each equilibrium error data-generating process.

The first step in testing linearity is to select the order of the AR. We follow Tsay (1989) in using the partial autocorrelation function (PACF) of y_t in selecting the appropriate lag order of the AR. Examination of the PACF of the equilibrium error revealed correlations up to the order two for y_{1t} and y_{2t} and up to four for y_{3t}. Accordingly the linearity tests are based on the artificial regressions (10.13) and (10.10) with p set equal to two for y_{1t} and y_{2t} and, set at four for y_{3t}. Tables 11.5-11.7 reports the tests of linearity. Based on the testing strategy described in Chapter 10, section 10.4, these results provide strong evidence of non-linearity for each of the equilibrium errors. For the first two equilibrium errors (y_{1t} and y_{2t}) the F-test F_L^{**} rejects linearity at the near zero percent level for a delay of one (d=1). Moreover, the F_L^{**}, F_L^{*}, and F_k strongly suggest that an ESTAR(2) model with d=1 and $\kappa^{*}=c^{*}=0$ is the most appropriate parameterization.

For the log price-dividend ratio, y_{3t}, F_L^{**} also rejects linearity at the near zero percent level for d=5 and, together with the F_k and F_L^{*} tests, strongly suggest that an ESTAR(4) model is the most appropriate. For completeness, Tables 11.5-11.7 also report the F-tests, F_L, F_4, F_3, F_2 and F_0 and using the selection procedure suggested by Teräsvirta (1994) the same ESTAR models are unambiguously selected. The results from these latter F-tests also suggest an ESTAR(2) with d=1 for y_{1t} and y_{2t}, and an ESTAR(4) with d=5 for y_{3t}.

Table 11.5: P-Vales for the Linearity Tests of y_{1t} : AR(2)

	F_L^*	F_K	F_L^{**}	F_L	F_4	F_3	F_2	F_0
d=1	0.0001	0.7030	0.0000	0.0001	0.0763	0.0002	0.0341	0.2093
d=2	0.0016	0.2697	0.0006	0.0006	0.0455	0.0004	0.3743	0.0659
d=3	0.0640	0.0601	0.1965	0.0218	0.0520	0.2797	0.0418	0.0211
d=4	0.0011	0.2113	0.0005	0.0009	0.1119	0.0020	0.0541	0.1119
d=5	0.0505	0.6003	0.0145	0.1168	0.6843	0.0145	0.6144	0.7764
d=6	0.0479	0.3121	0.0263	0.0044	0.0097	0.0240	0.3487	0.0204
d=7	0.6205	0.5949	0.4496	0.5480	0.3128	0.6537	0.4088	0.4982
d=8	0.0013	0.3658	0.0003	0.0004	0.0316	0.0002	0.6677	0.0626

Note: The Linearity Test are based on the long-run equilibrium adjustment, specified as an AR(2) process - see equations (10.13) and (10.10). The long-run equilibrium adjustment is given by $y_{1t} = Q_t - 4.9844 - 133.8047\ D_t$. The sample period is 1926i-1995iv.

Table 11.6: P-Vales for the Linearity Tests of y_{2t} : AR(2)

	F_L^*	F_K	F_L^{**}	F_L	F_4	F_3	F_2	F_0
d=1	0.0000	0.6486	0.0036	0.0000	0.0786	0.0000	0.0449	0.2016
d=2	0.0009	0.0601	0.0015	0.0017	0.2659	0.0005	0.2031	0.0825
d=3	0.0036	0.0015	0.2720	0.0100	0.5397	0.2505	0.0016	0.0067
d=4	0.0059	0.1319	0.0054	0.0039	0.0962	0.1471	0.0048	0.0680
d=5	0.0290	0.1617	0.0279	0.0472	0.3709	0.0068	0.6831	0.2292
d=6	0.5862	0.6609	0.3662	0.0005	0.0000	0.6482	0.3735	0.0002
d=7	0.0235	0.0702	0.0502	0.0260	0.2149	0.1771	0.0198	0.0787
d=8	0.0230	0.1663	0.0206	0.0053	0.0294	0.0342	0.1014	0.0307

Note: See Table 11.5. The long-run equilibrium adjustment is given by the demeaned y_{2t}, with $y_{2t} = Q_t - 164.351\ D_t$.

Table 11.7: P-Values for the Linearity Tests of y_{3t} : AR(4)

	F_L^*	F_K	F_L^{**}	F_L	F_4	F_3	F_2	F_0
d=1	0.3308	0.7903	0.1126	0.3434	0.3761	0.1613	0.6353	0.6530
d=2	0.0831	0.2667	0.0671	0.2768	0.9702	0.0207	0.6817	0.6803
d=3	0.7050	0.5418	0.6662	0.5036	0.2171	0.5668	0.6387	0.3520
d=4	0.0296	0.0728	0.0754	0.0090	0.0505	0.0159	0.3089	0.0209
d=5	0.0001	0.8867	0.0000	0.0004	0.5697	0.0000	0.2308	0.8489
d=6	0.0555	0.8560	0.0074	0.0253	0.0879	0.0334	0.3199	0.3029
d=7	0.1451	0.6153	0.0492	0.2126	0.4848	0.2115	0.1776	0.6331
d=8	0.3186	0.1435	0.6638	0.2979	0.3133	0.2846	0.3725	0.1700

Note: See Table 11.5. The long-run equilibrium adjustment is given by the demeaned log price-dividend ratio, $y_{3t} = q_t - d_t$. The artificial regressions, (10.13) and (10.10), used to calculate the linearity F-tests are based on p set equal to four.

11.5 ESTAR Estimation Results

We report the parsimonious form of the estimated ESTAR model for each of the equilibrium errors. The results from the three cases are similar.

(i) Residual from the OLS estimation of the cointegrating relationship

$$y_{1t} = Q_t - 4.9844 - 133.8047\, D_t$$

is found to reject linearity when modelled as a AR(2) process. Moreover, the linearity test favours modelling y_{1t} as a ESTAR(2) model with a delay of one. The results from the modelling y_{1t} as an ESTAR(2) process indicated substantial autoregressive conditional heteroscedasticity (ARCH) (Engle, 1982) and non-normality. Therefore, there exists additional non-linearity that the ESTAR model does not model and, thus, the ESTAR model is misspecified.[119] We model y_{1t} as an ESTAR(2)-ARCH(1) process. In estimating the non-linear model we follow Teräsvirta (1994) and standardize the exponent of the transition function F by dividing it by, σ_y^2, the the sample variance of y_t and choosing a starting value for (standardized) γ^* equal to 1. The estimated non-linear model is

$$\begin{aligned} y_{1t} = {} & \underset{\substack{(0.1183)\\ \{6.4117\}}}{0.7587}\, y_{1t-1} + \underset{\substack{(0.0615)\\ \{3.9918\}}}{0.2456}\, y_{1t-2} \\ & + [\underset{\substack{(0.1983)\\ \{-4.4204\}}}{-0.8765}\, y_{1t-1}]\times[1 - \exp\{-\underset{\substack{(0.0389)\\ \{2.3229\}}}{0.0904}\, y^2_{1t-1}/\sigma_1^2\}] + \hat{u}_t \end{aligned}$$

[119]Eitrheim and Teräsvirta (1996) suggest that non-linear models can be misspecified if there exists any remaining non-linearity that is not modelled.

$$\begin{aligned}\mathrm{Var}(\hat{u}_t) &= \underset{\substack{(0.0557)\\ \{11.7788\}}}{0.6563} + \underset{\substack{(0.0531)\\ \{2.2037\}}}{0.1170}\ \hat{u}^2_{t-1}\end{aligned}$$

$R^2 = 0.5225$ $\quad$ DW $= 2.0742$ $\quad$ JB $= 57.4938$

s $= 0.8966$ $\quad$ $\sigma^2_1 = 1.6714$ $\quad$ LR(2) $= 0.1651$

VR(2) $= 0.9722$

The figures in parenthese are standard errors and t-ratios are given in braces. The diagnostic statistics are those from regressing the derived fitted values of y_{1t} from the ESTAR-ARCH against actual y_{1t}. R^2 is the proportion of the variation in y_{1t} explained by the model; σ^2_1 is the sample variance of y_{1t}; DW is the Durbin-Watson statistic; JB is the Jarque-Bera (1980) normality test statistic; s is the standard error of the regression; VR(m) is the ratio of the residual standard error of the estimated model to that of a linear AR(m) model. The JB statistic is distributed as $\chi^2(2)$ under the null hypothesis of Gausian errors. LR(m) denotes a likelihood ratio statistic for the parsimonous restrictions implicit in the estimated model. With the exception of the normality test, all of the test statistics are insignificant at least at the five percent nominal level of significance. The ratio VR is high indicating only a small reduction, of the magnitude of 3 percent, in the unexplained component of the behaviour of the equilibrium error. The non-normality of the residuals is due to the large turbalances in the series in the pre-war period which is only partially captured by the ESTAR-ARCH parameterization. Moreover, the linear AR(2) model do even worse.

The dynamics of the model are interesting. The parameter values of the ESTAR(2)-ARCH(1) model suggest that equilibrium error is a near random walk when it is close to equilibrium but strongly mean-reverting when it moves away from the equilibrium. Furthermore, the speed of adjustment is in most cases quite slow. The scatter plot of the estimated transition function against y_{1t-1}, given in Figure 11.2, shows most of the observations clustered in range for F between 0 and 0.2. Since none of the observations appear to approach the outer limit F=1, for large deviations from equilibrium there is little evidence of a fast adjustment back towards the OLS estimated equilibrium error.

(ii) Cointegrating residual from Johansen ML estimation

$$y_{2t} = Q_t - 164.351D_t$$

is also found to reject linearity when modelled as a AR(2) process. The linearity test favours modelling y_{2t} as a ESTAR(2) model with a delay of one. As in the previous case, the results from the modelling the demeaned y_{2t} as an ESTAR(2) process indicated substantial ARCH. To account for this ARCH effect we modelled the demeaned y_{2t} as an ESTAR(2)-ARCH(1) process. The estimated parsimonious non-linear model is

$$\begin{aligned}
y_{2t} = {} & \underset{\substack{(0.1377)\\ \{5.9932\}}}{0.8251}\, y_{2t-1} + \underset{\substack{(0.0559)\\ \{3.7002\}}}{0.2067}\, y_{2t-2} \\
& + [\underset{\substack{(0.2039)\\ \{-4.3171\}}}{-0.8802} y_{2t-1}]\times[1 - \exp\{-\underset{\substack{(0.0655)\\ \{2.4736\}}}{0.1619}\, y^2_{2t-1}/\sigma_2^2\}] + \hat{u}_t
\end{aligned}$$

$$\mathrm{Var}(\hat{u}_t) = \underset{\substack{(0.0690)\\ \{12.1551\}}}{0.8386} + \underset{\substack{(0.0629)\\ \{2.4032\}}}{0.1511}\ \hat{u}^2_{t-1}$$

R^2	$= 0.4571$	DW	$= 2.1066$	JB	$= 71.3397$
s	$= 1.0198$	σ_2^2	$= 1.8987$	LR(2)	$= 0.2539$
V	$= 0.9519$				

The results for the Johansen ML estimated equilibrium error are similar to the OLS cointegrating error. With the exception of the normality test, all of the test statistics are insignificant at least at the five percent nominal level of significance. The ratio VR indicates a reduction of only 4.5 percent in the unexplained component of the behaviour of the equilibrium error.

The parameter values of the ESTAR(2)-ARCH(1) model suggest that equilibrium error is random walk or midly explosive when it is close to equilibrium and strongly mean-reverting when it moves substantially away from its equilibrium. A scatter of the transition function against demeaned y_{2t-1} indicates that the speed of adjustment is slow (Figure 11.3).

(iii) The log real stock price-dividend is given by

$$y_{3t} = q_t - d_t$$

is found to reject linearity when modelled as a AR(4) process. The linearity test favours modelling y_{3t} as a ESTAR(4) model with a delay of five. As in the previous cases, there is substantial ARCH effects present in the ESTAR(4) model. For this reason we modelled the demeaned y_{3t} as an ESTAR(4)-ARCH(1) process. The estimated non-linear model is

$$y_{3t} = \underset{\{8.0205\}}{\underset{(0.0930)}{0.7456}}\, y_{3t-1} + \underset{\{4.1686\}}{\underset{(0.0656)}{0.2735}}\, y_{3t-2} - \underset{\{-2.6635\}}{\underset{(0.0634)}{0.1690}}\, y_{3t-3} + \underset{\{5.4664\}}{\underset{(0.0556)}{0.30539}}\, y_{3t-4}$$

$$+ \; [\underset{\{-4.3875\}}{\underset{(0.1413)}{-0.6201}}\, y_{3t-1}] \times [1 - \exp\{-\underset{\{3.2760\}}{\underset{(0.1100)}{0.3605}}\, y^2_{3t-5}/\sigma_3^2\}] + \hat{u}_t$$

$$\mathrm{Var}(\hat{u}_t) = \underset{\{7.9361\}}{\underset{(0.0021)}{0.0164}} + \underset{\{3.9477\}}{\underset{(0.1024)}{0.4042}}\, \hat{u}^2_{t-1}$$

R^2	$= 0.7018$	DW	$= 1.9641$	JB	$= 39.6867$
s	$= 0.1600$	σ_3^2	$= 0.0847$	LR(4)	$= 7.2567$
V	$= 0.9617$				

The ratio VR indicates a reduction of less than 4 percent in the unexplained component of the behaviour of the equilibrium error. The other test statistics are similar to the previous two cases. The equilibrium error is midely explosive (or random walk) near the equilibrium and mean-reverting away from the equilibrium level and the speed of adjustment is in most cases quite slow as most of the observations are clustered in the range for F between 0 and 0.4 (Figure 11.4).

Evidence of a non-linear equilibrium error is supported by the Monte Carlo simulations results reported in Table 11.8. The parameter values from the three ESTAR-ARCH equilibrium error models are used to simulate three equilibrium errors. The number of simulations is 500. The Monte Carlo is designed to select, for each simulation, the appropriate lag length for the AR(p) using the PACF approach and also selects the delay parameter, d (for d=1,...8), which minimises the P-value of the F_L^* linearity test.

The F_L^* test rejects linearity in favour of an ESTAR model 89.8 percent of time for the simulated y_{1t} equilibrium error series. The median P-value of 0.0008 strongly rejects non-linearity. A similar result is also found for the simulated y_{2t} series. Furthermore, the F_L, F_4, F_3, F_2, and F_0 test statistics are consistent with the F_L^*, F_K, and F_L^{**} test statistics. The evidence against non-linearity in favour of an ESTAR representation is not as strong in the simulated log stock price-dividend ratio series. Although the median P-value of the F_L^* test is 0.0298, only 60.4 percent of the time is linearity rejected at the 5 percent level.

Table 11.8: Monte Carlo Results: Median P-Values

	F_L^*	F_K	F_L^{**}	F_L	F_4	F_3	F_2	F_0
(i) y_{1t}	0.0008 (89.8)	0.3579 (15.4)	0.0005 (92.8)	0.0013 (85.8)	0.4508 (11.2)	0.0005 (92.8)	0.3608 (16.0)	0.3545 (18.4)
(ii) y_{2t}	0.0001 (96.0)	0.3810 (15.8)	0.0001 (97.0)	0.0002 (93.4)	0.4217 (12.0)	0.0001 (96.8)	0.3059 (18.0)	0.3457 (19.6)
(iii) y_{3t}	0.0298 (60.4)	0.2904 (15.0)	0.0192 (65.2)	0.0376 (56.8)	0.3701 (13.2)	0.0221 (63.4)	0.2885 (16.4)	0.2633 (18.2)

Notes: Figures in parentheses are the percentage of times that the P-value was less than 0.05. The sample period is 273 usable observations. The number of simulations is 500.

Figure 11.2: Transition Function: F[y(t-1)] against y(t-1)

OLS Estimation of the Equilibrium Error

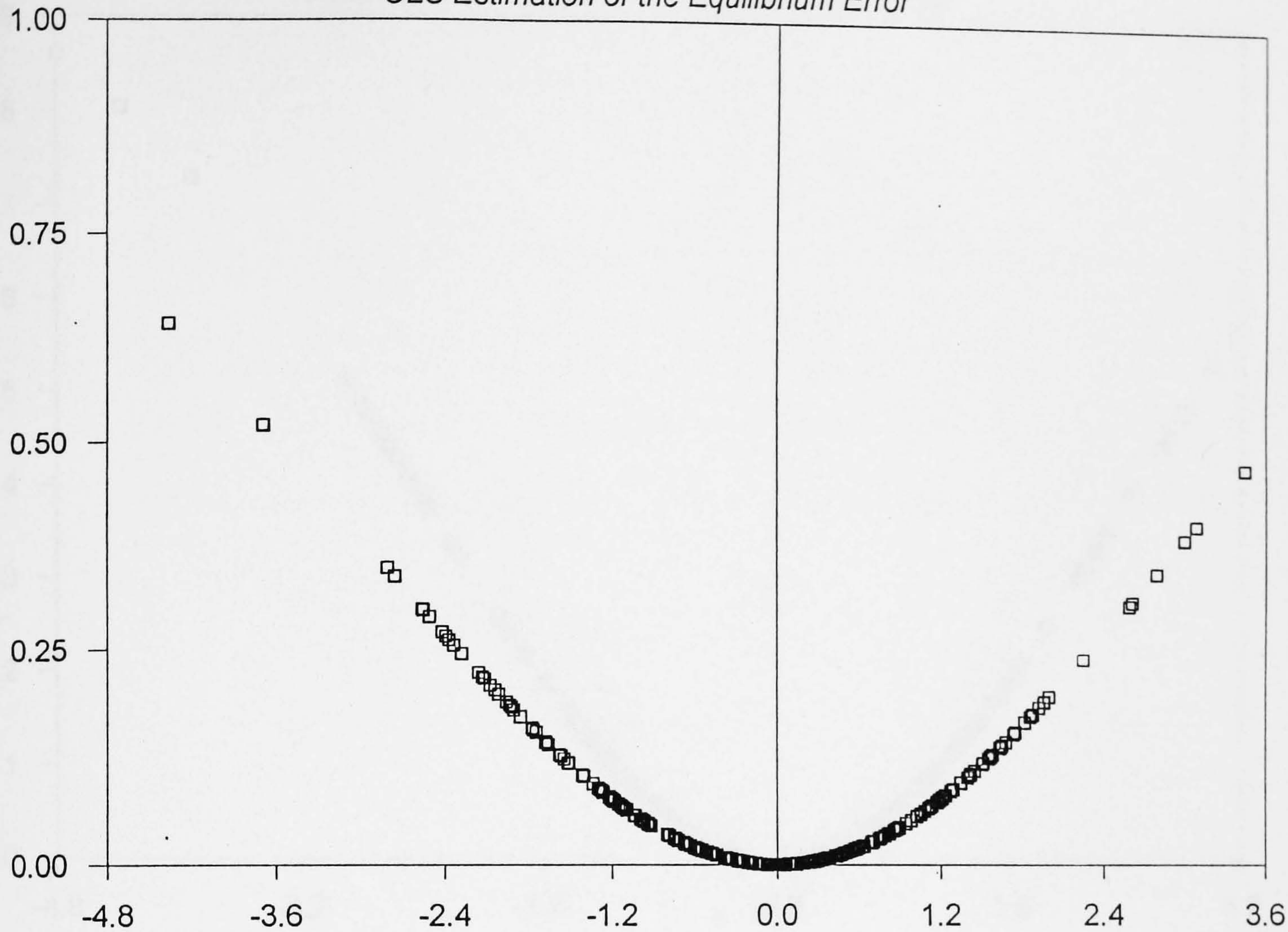


Figure 11.3: Transition Function: F[y(t-1)] against y(t-1)

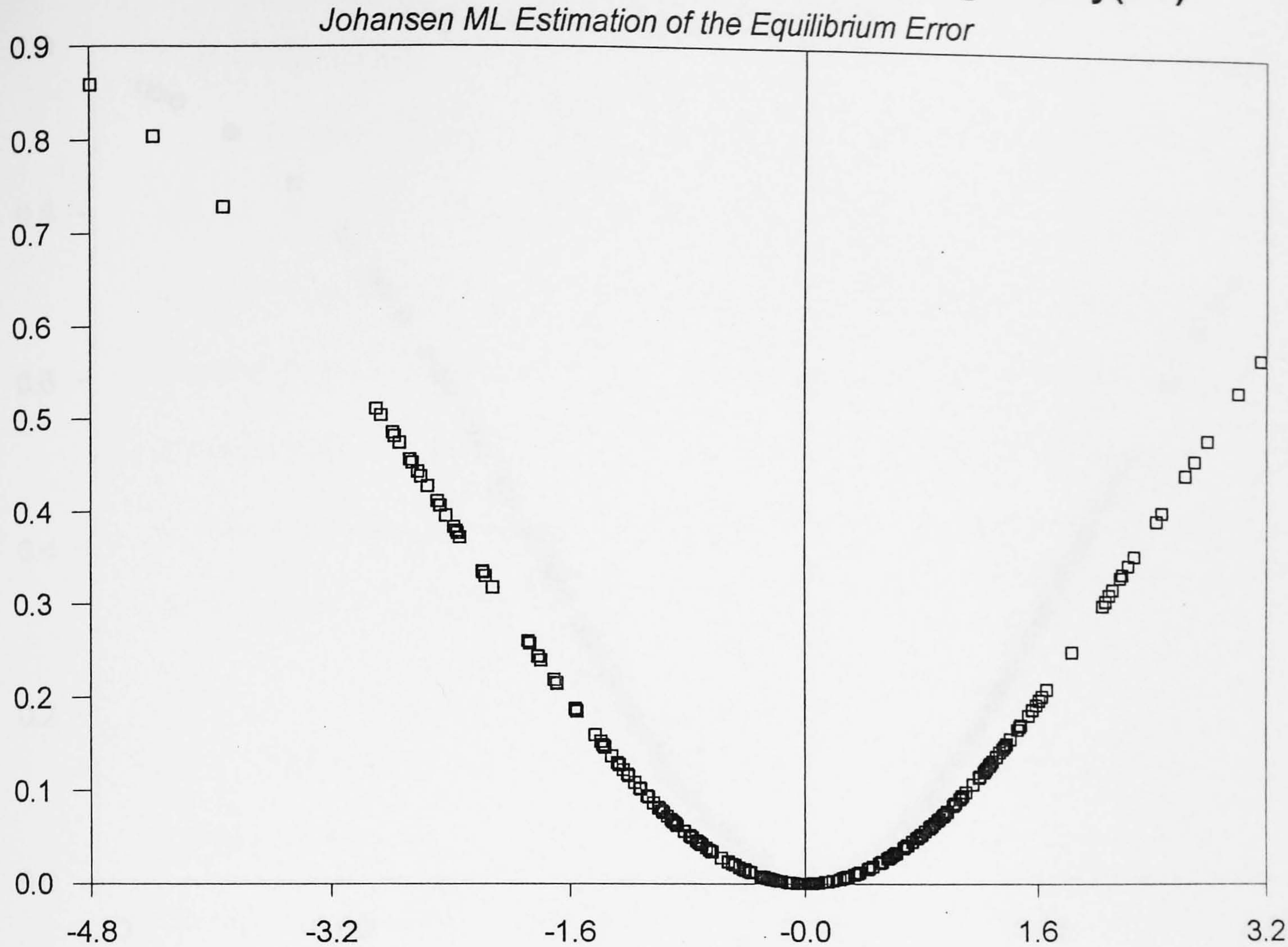
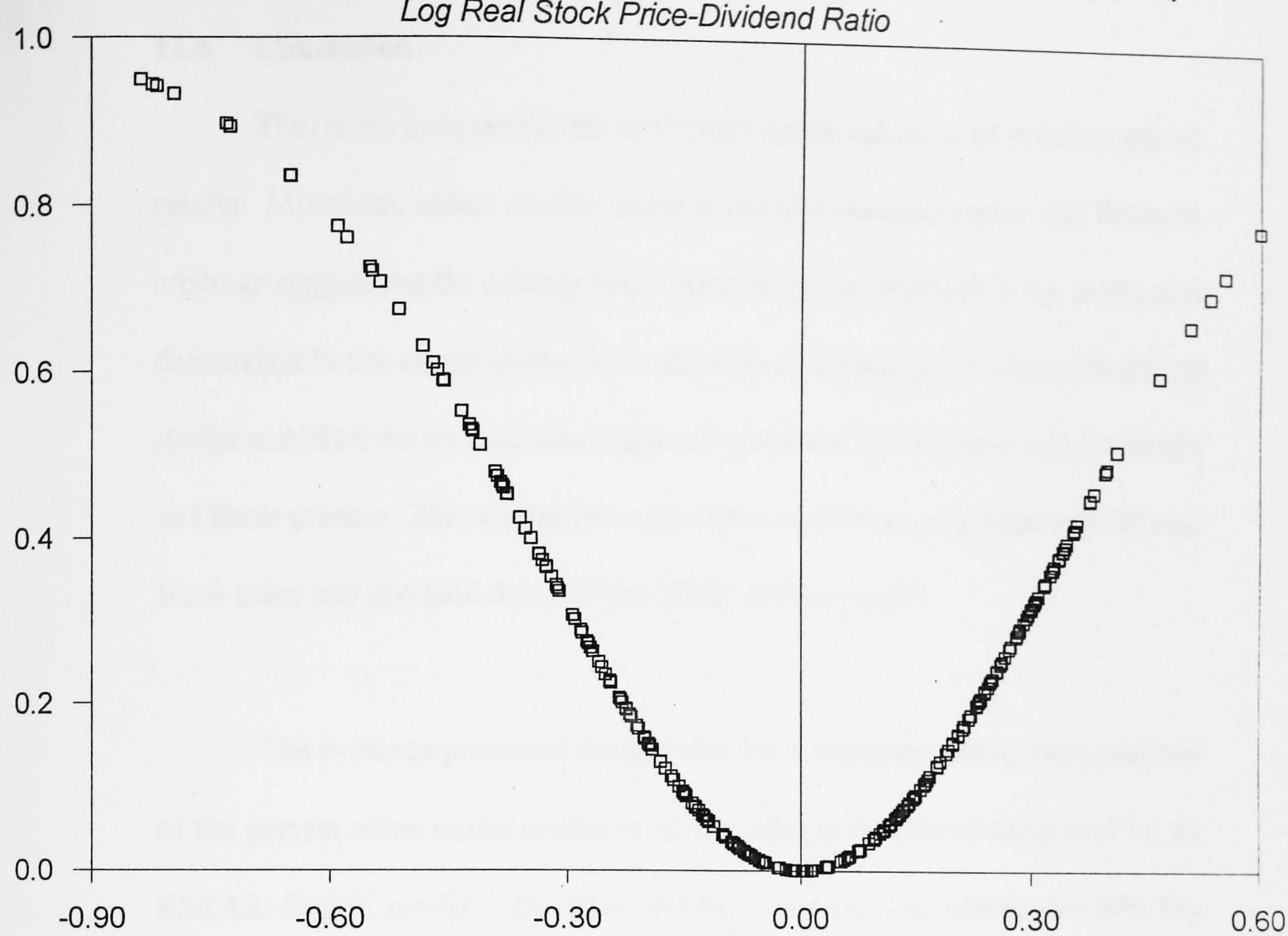


Figure 11.4: Transition Function: F[y(t-5)] against y(t-5)



11.6 Conclusion

The results from tests of the traditional present value model produce mixed results. Moreover, recent studies on the effect of transaction costs and limits to arbitrage suggest that the cointegrating relationship between real stock prices and dividends is better approximated by a non-linear adjustment. Previous empirical studies modelled the cointegrating relationship between stock prices and dividends as a linear process. This chapter provides empirical evidence for quarterly US real stock price and dividend data, for the 1926i-1995iv period.

The evidence presented reveals that the estimated cointegrating residual of the present value model (either in levels or logs) is approximated well by an ESTAR-ARCH model. In other words, the error correction towards the cointegrating equilibrium implied by the present value model is non-linear. The parameters of the non-linear model imply random walk behaviour for small deviations and fast mean-reverting adjustment for large deviations from equilibrium. This finding is consistent with features of the stock market, such as transaction costs and limits to arbitrage. The results are strongly supported by Monte Carlo evidence.

A potential extensions of this work that is likely to yield interesting insights in the nature of stock price behaviour is an examination of the relative forecasting performance of non-linear error correction models implied by the non-linearity in the deviations from the present value equilibrium against linear alternatives.

Chapter 10

SUMMARY AND CONCLUSION

The analysis of the various theoretical and empirical issues investigated in this thesis contributes to the expanding literature on the linkages between macroeconomic time series and stock price behaviour. The central theoretical focus is a macroeconomic model with overlapping nominal wage contracts and a stock price determination equation derived from the present value model of stock prices. The model is essentially neoclassical - consistent with the traditional aggregate demand and aggregate supply model with a long-run vertical aggregate supply curve - and Fisherian in structure and also allows for reasonably complex dynamics. This model forms the underlying theoretical framework for much of the empirical work undertaken. We demonstrate that changes in real stock prices may be serially correlated even under the assumption of fully efficient markets in the sense that there are no profitable arbitrage opportunities between current and expected stock price movements. Furthermore, aggregate demand shocks have only temporary effects on real stock prices, while supply shocks may affect the level of real stock prices permanently.

The empirical work employs recent econometric techniques. The dynamic interaction between real stock prices and macroeconomic shocks and investigating mean reversion in stock prices employs the Blanchard and Quah (1989) decomposition technique and robust estimation procedures. The multivariate decomposition technique is also employed in explaining the stock return-inflation puzzle. In testing and modelling the present value model we employ recent developments in non-linear time series modelling.

The fundamental feature of the Blanchard-Quah decomposition technique is that it imposes a long-run restriction on the VAR to identify the decomposition. The advantage of this technique is that, in the context of the macro model, the shocks are identified as the aggregate demand and supply shocks. Therefore, we can empirically investigate the effect of real stock prices to macroeconomic shocks. Furthermore, the non-normality characteristics associated with financial data creates difficulties for least squares estimation[120] and suggest that robust estimation procedures are more efficient. For this reason we also use two robust estimation procedures - the least absolute deviation procedure and, the more recent, residual augmented least squares approach - to decompose stock prices.

In Chapter 5, using a variant of the Blanchard-Quah decomposition to estimate the temporary and permanent components in real stock prices - where the temporary and permanent innovations to real stock prices are related to aggregate macroeconomic demand and supply innovations, respectively - the significance of a mean-reverting component in real stock prices in the US is investigated. Since the response of real stock prices to temporary innovations is zero, the temporary component is mean-reverting. Thus the procedure isolates a mean-reverting

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[120]LS estimation places a relatively heavy weight on outliers, and in the presence of errors that are not normally distributed can lead to estimates that are extremely fragile.

component in real US stock prices.

Monthly US real stock prices reveal a significant temporary component due to aggregate demand shocks that is mean reverting. Since the temporary component is significant then we can reject the random walk hypothesis in favour of mean-reversion hypothesis. We estimate that, for the post-war period, this mean-reverting component accounts for 44 percent of the variation of monthly real stock returns, and is statistically significant. Consistent with previous studies, we find that temporary innovations to real stock prices tend to be quite persistent, with a half-life of about 18 months.

The evidence of a substantial mean-reverting component in US stock prices is also consistent with those of more recent studies which have used vector autoregressive techniques to decompose stock prices into their temporary and permanent components (Cochrane, 1994; Lee, 1995). Moreover, as with these recent studies, the results are not subject to the recent controversy associated with long return horizon analysis (Richardson and Stock, 1989; Cecchetti *et al.*, 1990; Kim *et al.*, 1991; Mankiw *et al.*, 1991; Richardson, 1993).

Employing a similar multivariate innovation decomposition technique we have also investigated the interaction between macroeconomic shocks and real stock prices for sixteen countries, for the 1957-1995 period. This provides a broader perspective on the earlier US results. Aggregate demand and supply shocks are used to estimate a temporary and permanent component of real stock prices. The evidence supports the earlier US findings that real stock prices contain a statistically significant temporary component that is mean-reverting, explaining between 7 and 64 percent of the variation in quarterly real returns and thus that real returns are to some extent predictable (see, for example, Fama and French, 1988b; Campbell, 1990, 1991; Cochran *et al.*, 1993; Cochrane, 1994). The impulse response functions of a temporary shock on real stock prices shows, however, that, for some countries the mean-reverting component can be quite persistent, with a half life varying between 1 and 25 quarters.

The multi-country analysis emphasises that the dynamic response of stock prices to temporary and permanent shocks varies across markets.[121] A number of common features include, real stock prices rise in response to a permanent shock to stock prices and continue to rise for a number of years after the shock; the mean-reverting component is statistically significant at standard significance levels.

These results are consistent with those of previous researchers who have used vector autoregressive techniques to decompose stock prices into their temporary and permanent components (Cochrane, 1994; Lee, 1995). The response of consumer prices to temporary and permanent shocks is as predicted by the standard macroeconomic aggregate demand - aggregate supply model with a vertical long-run aggregate supply curve.

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[121]The different dynamic response of real stock prices suggests that there exists potential gains from international diversification.

The final essay on mean reversion, Chapter 7, builds on the earlier work in exploring the size and significance of the mean-reverting component in real stock prices in the post-war period, for the US and UK. Using a multivariate innovation decomposition method we have investigated the dynamic behaviour between real stock returns and changes in interest rates to estimate the temporary component of real stock prices. The underlying VAR in the decomposition was estimated using three estimation procedures: least squares, residual augmented least squares, and least absolute deviation.

The evidence supports the hypothesis that US and UK stock prices contain a statistically significant mean-reverting component, explaining around 25%, and 10%, of the variation in real stock price movements, for US and UK prices, respectively. Therefore, returns are to some extent predictable.

Out finding of a smaller, albeit statistically significant, mean-reverting component in UK stock prices is consistent with international studies. There is strong evidence, especially that of previous researchers who have used vector autoregressive techniques to decompose stock prices, that US stock prices contain a large mean-reverting component and our findings support this hypothesis. In contrast, previous results for UK stock prices which rely on variance ratio and the related regression-based tests which generate contrasting findings dependent on the sample period and the distribution properties of the variance ratio statistic. For example, Mills(1991, 1995) and Cochran and DeFina (1995) find that post-war UK stock prices contain a mean-averting component, in contrast Poterba and

Summers (1988) find a significant mean-reverting component that includes the WW II period.

The VAR approach we use is not subject to the overlapping data problems encountered in the long-horizon approaches and, in contrast to Mills (1991, 1995) and Cochran and DeFina (1995), identifies a significant mean-reverting component in UK stock prices that explains about 10 percent of stock price movements. It is noticeable that temporary shocks to UK real stock prices have a half-life of only one month - thus, the mean-reverting component is not at all persistent and is less unlikely to be identified using either a regression-based or a variance-ratio approach. Whereas, temporary shocks to US real stock prices tend to be quite persistent, with a half-life of seven months.

These findings are robust to alternative estimation procedures designed to allow for non-Gaussian disturbances. The RALS estimation procedure yields substantial efficiency gains of over 20 percent compared to LS estimation. The non-normality in the least squares VAR residuals causes the size of the mean-reverting component to be underestimated. The RALS procedure estimates that, for the US, 30 percent of the variation in real stock price movements can be explained by temporary shocks. The LAD procedure estimates that 40 percent of the variation in real stock price movements can be explained by the mean-reverting component. The RALS and LAD procedures estimate only a slightly higher mean-reverting component that the LS procedure. Thus, the LS qualitative findings appear to be robust to the outliers in the VAR residual distributions.

The association between a significant mean-reverting component and predictability of stock returns has several potential implications for the practical investor. First, the evidence of mean reversion implies that real stock returns are to some degree predictable. It is worth noting that stock returns are more strongly forecastable in the post-war period due to the high variability that surrounds the Great Depression and WW II period (Campbell, 1990, 1991: Cochrane, 1994). Second, in the presence of mean reversion, an investor with a relative risk aversion coefficient of less (greater) than unity will invest less (more) in equities as his investment horizon increases (Samuelson, 1991). Moreover, the presence of a mean-reverting component suggests using a portfolio strategy of going long in equities that have recently declined in value.

The reason for the significant mean-reverting component in stock prices is not obviously clear, a plausible explanation is provided by noise traders in markets (De Long *et al.*, 1990). Also, the issue of whether mean reversion reflects market inefficiency is debatable and - linked to joint hypothesis problem - is unlikely to be easily resolved. For a comparison of thought see De Long *et al.* (1990) who show that mean reversion is consistent with noise trader risk and Fama and French (1988a) who argue that mean reversion may also result form the workings of efficient markets. However, it is market microstructure analysis that is likely to provide further insights into the explanation of mean reversion and the predictability of stock prices (O'Hara, 1995). Furthermore, the approach, and previous approaches, has necessarily limited itself to the study of linear (or, more precisely, log-linear) persistence in stock prices. Future research might profitably study the presence of predictable non-linearities in stock price behaviour.[122]

There are a number of competing theories that purport to explain the observed negative relationship between inflation and stock returns. In the context of the macro model with overlapping wage contracts, we show that the negative relationship is attributed to inflation due to aggregate supply innovations. Real stock returns is not correlated with inflation due to aggregate demand innovations. This finding is consistent with Fama's (1981) proxy hypothesis explanation. Monte Carlo simulations of the model support this finding.

The theoretical and empirical investigation of the observed correlation between US inflation, real activity and real stock returns was carried in Chapter 9. Using a multivariate innovation decomposition method - and the macro model to identify the innovations - we purged the output and consumer price series of, alternately, movements over the sample period due to aggregate supply innovations and movements due to aggregate demand innovations. The counterfactual series were then used to investigate the stock return-inflation puzzle in the context of inflation and output series generated by fluctuations in aggregate supply (real economic activity fluctuations) and by fluctuations in aggregate demand (monetary fluctuations).

The negative correlation between inflation and real stock returns were

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[122]Tong (1990) reports evidence of non-linearity in a number of stock price series.

found to depend on the source of inflation; i.e. whether it is due to aggregate demand or aggregate supply innovations. This finding supports Fama's proxy hypothesis as an explanation of the stock return-inflation puzzle. Moreover, the relationship between real stock returns and inflation due to aggregate demand innovations is insignificantly different from zero - supporting the Fisher hypothesis. Also, as suggested by the proxy hypothesis, real stock returns are strongly negatively related with the portion of inflation due to aggregate supply innovations. Real stock returns and real output growth are significantly positively related when output is due to aggregate supply innovations and not aggregate demand innovations.

Linear models are likely to be too restrictive to adequately capture asymmetries that are likely to exist in modelling financial time series. Evidence of this is provided by market microstructure aspects of financial markets, for example, limits to arbitrage and transaction costs. A parsimonious parametric non-linear model which has shown to approximate well a broad range of non-linearity is the smooth transition autoregressive (STAR) models. A special case of the STAR family is the exponential smooth transition autoregressive (ESTAR) model and is appropriate in modelling a potential nonlinear feature of stock price behaviour. That is, stock prices may follow a unit root process when prices are close to their long-run equilibrium (or fundamental value) and only mean-revert when prices are substantially away from their long-run equilibrium, while the speed of adjustment towards equilibrium varies directly with the extent of the deviation from equilibrium. Recent developments in non-linearity modelling - in particular STAR models - are appropriate in modelling stock price adjustment to long-run equilibrium

The findings of the empirical tests of the traditional present value model are mixed. Moreover, recent studies on the effect of transaction costs and limits to arbitrage suggest that the cointegrating relationship between real stock prices and dividends is better approximated by non-linear adjustment. Previous empirical studies modelled the cointegrating relationship between stock prices and dividends as a linear process. This chapter provides empirical evidence for quarterly US real stock price and dividend data, for the 1926i-1995iv period.

The evidence presented reveals that the estimated cointegrating residual of the present value model (either in levels or logs) is approximated well by an ESTAR-ARCH model. In other words, the error correction towards the cointegrating equilibrium implied by the present value model is non-linear. The parameters of the non-linear model imply near unit root behaviour for small deviations and fast mean-reverting adjustment for large deviations from equilibrium. This finding is consistent with features of the stock market, such as transaction costs and limits to arbitrage. The results are further supported by Monte Carlo evidence.

A potential extensions of this work that is likely to yield interesting insights in the nature of stock price behaviour is an examination of the relative forecasting performance of non-linear error correction models implied by the non-linearity in the deviations from the present value equilibrium against linear alternatives.

Another extensions to the present work is that the simple macro model could be expanded to include a time-varying real interest rate. This would also serve as to identify the restrictions on a three variable VAR of real stock prices, real interest rates, and consumer prices.

It would also be of interest to estimate the size of the mean-reverting component due to aggregate demand shocks relative to the mean-reverting component when the pure random-walk component is extracted from real stock prices. This requires that all the restrictions associated with equation (4.10) need to be identified. Although such an exercise is technically difficult, it would allow a direct comparison of previous studies on mean reversion and also provide the degree to which the mean-reverting component is explained by aggregate demand shocks.

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