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Stock Prices, Inflation and Stock Returns Predictability

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Abstract

This paper considers a new perspective on the relationship between stock prices and inflation, by estimating the common long-term trend in real stock prices, as reflected in the earning-price ratio, and both expected and realized inflation. We study the role of the transitory deviations from the common trend in the earning-price ratio and realized inflation for predicting stock market fluctuations. In particular, we find that these deviations exhibit substantial in-sample and out-of-sample forecasting abilities for both real stock returns and excess returns. Moreover, we find that this variable provides information about future stock returns at short and intermediate horizons that is not captured by other popular forecasting variables.

Keywords: Time-Varying Expected Returns, Stock Return Predictability, Stock Return-Inflation puzzle.
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1. Introduction

There now exists a large literature documenting the predictability of stock returns from past information. Researchers have identified a number of financial variables that are useful in predicting future stock returns. These include the dividend-price ratio (Rozeff, 1984; Campbell and Shiller, 1988a; Fama and French, 1988; Hodrick, 1992), the price-earning ratio (Campbell and Shiller, 1988b, 1998), the book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998; Lewellen, 2004), the dividend payout ratio (Lamont, 1998), the term and default spreads on bonds (Keim and Stambaugh, 1986; Campbell, 1987; Fama and French, 1989), recent changes in short-term interest rates (Campbell, 1987; Hodrick, 1992; Ang and Bekaert, 2004), the equity share in total new equity and debt issues (Baker and Wurgler, 2000), the level of consumption relative to income and wealth (Lettau and Ludvigson, 2001) and the aggregate stock market volatility in conjunction with these consumption-asset-labor deviations (Guo, 2006). Many of these variables are related to the stage of the business cycle (Fama and French, 1989; Lettau and Ludvigson, 2001). Typically, expected returns and business conditions move in opposite directions.

In this paper, we provide new evidence of the in-sample and out-of-sample predictability of stock returns. We find that the transitory deviations from the common trend in the earning-price ratio and inflation provide useful information for predicting both real stock returns and excess returns.

Dividends, earnings (or multiyear backward moving averages of earnings), book value are traditionally used to normalize stock prices. As noted by Lamont (1998), the important variable is the level of stock prices which predicts future returns because stock prices are presumed mean-reverting, even though the persistence of valuation ratios implies that such restorations took many years to take shape. Indeed, Fama and French (1988), Campbell and Shiller (1988a,b), Valkanov (2003) and Lewellen (2004), among others, find that valuation ratios are positively correlated with subsequent returns and that the implied predictability of returns is substantial at longer horizons. Since dividend yield only weakly predicts dividend growth, the variation of dividend yields must be due to changing forecasts of expected returns[1]. Also, Campbell and

[1] As noted by Campbell and Thompson (2004), these results are consistent with the view of value-oriented investors in the tradition of Graham and Dodd (1934) that high valuation ratios are an indication of an undervalued stock market and should predict high subsequent returns.

Shiller (1998) and Rapach and Wohar (2004a) find that these ratios are useful in predicting future growth in real stock prices at long, but not short-horizons, using annual data spanning 1872-1997[2].

Despite the econometric difficulties relating to the overlapping observations, highly persistent predictor variables, small samples biases in predictive regressions (Mankiw and Shapiro, 1986; Stambaugh, 1986, 1999; Richardson and Stock, 1989; Nelson and Kim, 1993, Kirby, 1997, Ferson et al., 2003), the consensus – after thirty years of empirical works – appears to be that aggregate returns do contain an important predictable component (Cochrane, 1999; Campbell, 2000).

However, several recent studies have cast doubt on the predictability of stock returns, especially from the dividend yield at long-horizons. On the one hand, Bossaerts and Hillion (1999) and Goyal and Welch (2003, 2004) pointed out that the wide range of variables presented above have some in-sample predictability but exhibit weak or no out-of-sample predictive power[3]. On the other hand, Valkanov (2003), Campbell and Yogo (2004), Torous et al. (2005) reexamine the evidence for predictability using tests that have the correct size even if the predictor variable is highly persistent[4] and find that the predictive power of the dividend yield at long-horizons is considerably weakened. Moreover, Ang and Bekaert (2004) show, after accounting for small sample properties of the standard tests, that at long horizons, excess return predictability by the dividend-price ratio is not statistically significant, not robust across countries and not robust across different sample periods. They argue that the ability of the dividend yield to predict excess returns is best visible at short horizons with the short rate as an additional regressor.

These new results could be explained by the fact that the valuation ratios are not mean reverting, especially in the recent period, and therefore non-stationary contrary to the Campbell and Shiller (1998) hypothesis. Indeed, Goyal and Welch (2003), among others, cannot reject that dividend yield contain an unit-root over the longest sample period available at quarterly

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[2] For example, Campbell and Shiller (1998) present scatterplots and R^2 measures that indicate a weak ability for the price-dividend and price-earning ratios to forecast real stock price growth over the next year, but a strong and significant ability to forecast real stock price growth over the next ten years.

[3] Campbell and Thompson (2004) show that the findings of Goyal and Welch (2004) are no longer valid, once sensible restrictions are imposed on the signs of coefficients and return forecasts.

[4] Stambaugh (1999), among others, has shown that the apparent predictability of stock returns may be spurious when the predictor variable is persistent and its innovations are highly correlated with returns.

frequency (since 1926)[5]. In the present value model, non-stationary dividend-price ratio or non-stationary linear combination of stock prices and dividends implies an explosive bubble (Campbell and Shiller, 1987; Diba and Grossman, 1988). On the other hand, valuation ratios might exhibit other forms of non-stationarity that do not imply explosive bubble. Indeed, Timmerman (1995) shows that when the expected rate of return varies over time, the present-value model does not generally imply the existence of a stationary relationship between stock prices and dividends. Also, Carlson, Pelz and Wohar (2002) employ breakpoint tests on the means of the quarterly valuation ratios and find evidence of one downward break in the dividend-price ratio and the earning-price ratio at the beginning of the 1990's. Finally, several authors suggested that the equity premium dropped sharply over the last twenty years (e.g. Jagannathan, McGrattan, and Scherbina, 2000; Fama and French, 2002). If this drop is permanent, then this implies a permanent drop in the dividend-price ratio.

In this paper, we assume a time-varying risk premium which can be expressed as a linear function of the expected inflation. We study the role of the transitory deviations from the common trend in the earning-price ratio and inflation for predicting stock market fluctuations. In particular, we find that these "trend deviations" exhibit substantial in-sample and out-of-sample forecasting abilities for both real stock returns and excess returns. Moreover, we find that the residual from the cointegrating relation among the earning-price ratio and inflation provides information about future stock returns at short and intermediate horizons (from 1 to 12 quarters) that is not captured by other popular forecasting variables.

The use of our forecasting variable is motivated by the vast empirical literature that has emphasized the significant negative correlation – in post-war data for the US and other industrialized countries – between inflation and stock returns (e.g. Fama and Schwert, 1977; Gultekin, 1983; and more recently Barnes et al., 1999) and between inflation and the level of real stock prices, as reflected in dividend-price ratio and price-earning ratios (Modigliani and Cohn, 1979; Feldstein, 1980; and more recently, Sharpe, 2002; Campbell and Vuolteenaho, 2004).

The paper proceeds as follows: Section 2 reviews previous research on the negative relationship between stock returns/stock prices and inflation. Section 3 presents results of estimating the trend relationship among the earning-price ratio and inflation. Section 4 discusses

[5] Also, ADF and KPSS tests indicate that valuation ratios contain an unit-root over the longest sample period available at annual frequency (1871-2003).

data used in our forecasting regressions for stock returns and presents some summary statistics. Section 5 and 6 report respectively the in-sample and out-of-sample predictability test results. Section 7 shows long-horizon forecasting results. Section 8 concludes.

2. Stock Prices and Inflation

The observed negative relationship between common stock returns and various measures of expected and unexpected inflation during the post-World War II period is "troublesome" because it appears to contradict Fisher's (1930) hypothesis, which states that nominal asset returns move one-for-one with the expected inflation so that real stock returns are determined by real factors independently of the rate of inflation. According to Fisher (1930), assets which represent claims to physical or real assets, such as stocks, should offer a hedge against inflation.

The inflation-stock return correlation has been subjected to extensive study at the end of 1970s and the beginning of 1980s (e.g. Lintner, 1975; Bodie, 1976; Fama and Schwert, 1977; Jaffe and Mandelker, 1976; Nelson, 1976; Fama, 1981; Pyndick, 1984)[6] and was confirmed more recently (Graham, 1996; Siklos and Kwok, 1999; Barnes et al., 1999).

In analyzing the Fisher hypothesis most of these empirical studies have focused on asset returns over relatively short time horizons (less than a year). However, Boudoukh and Richardson (1993) investigate the relation between stock returns and inflation at both short (1 year) and long (5 year) horizons using long-term annual US and UK data, and obtain the quite interesting result that at the 1-year horizon nominal stock returns and inflation are approximately uncorrelated, while at the 5-year horizon the Fisher equation holds.

Other early studies focused on the negative relationship between inflation and the level of real stock prices, as reflected in dividend-price ratio and price-earning ratio (Modigliani and Cohn, 1979; Feldstein, 1980). More recently, Ritter and Warr (2002), Sharpe (2002) and Campbell and Vuolteenaho (2004) confirmed this negative relation.

A number of alternative hypotheses have been advanced in the literature to explain the negative relation between inflation and stock prices and/or stock returns. These alternatives

[6] Most of these studies uses US data, but empirical evidence is also provided at the international level (e.g. Firth, 1979; Solnik, 1983; Gultekin, 1983, Boudoukh and Richardson, 1993).

include: (i) a correlation between expected inflation and expected real economic growth (the "proxy hypothesis" suggested by Fama, 1981) ; (ii) the hypothesis that investors may irrationally discount real cash flows using nominal interest rates (Modigliani and Cohn, 1979); (iii) changes in the expected return and risk aversion (i.e. the equity risk premium) and (iv), the inflation non-neutralities tax code which distorts accounting profits (Feldstein, 1980).

The "proxy hypothesis" suggested by Fama (1981) claims that the negative stock return-inflation relation is spurious. The anomalous stock return-inflation relation is in fact induced by a negative relation between inflation and real activity. Fama's hypothesis predicts that rising inflation rates reduce real economic activity and demand for money[7]. Geske and Roll (1983) proposes a "reverse causality" explanation and argue that a reduction in real activity leads to an increase in fiscal deficits. Since the Federal Reserve bank monetizes a portion of fiscal deficits, the money supply increases, which in turn increases inflation.

The empirical evidence of the "proxy hypothesis" is mixed and suggests that it is not a complete explanation. Kaul (1987) find some support for the proxy hypothesis, however the findings of Cochran and DeFina (1993) and Caporale and Jung (1997) did not support it. Lee (1992) and Balduzzi (1995) find strong support for the proposition that more than the proxy hypothesis is at work and particularly that the rate of interest accounts for a substantial share of the negative correlation between stock returns and inflation. Sharpe (2002) finds that the negative relation between inflation and P/Es is attributable partly to lower forecasted real earnings growth. Also, the "reverse causality hypothesis" is supported by James, Koreisha, and Partch (1985) but rejected by Lee (1992).

Alternatively, Modigliani and Cohn (1979) suggest that investors collectively suffer from money illusion and commit two errors in valuing equities: they use a nominal rate to discount real cash flows (and fail to adjust nominal growth rate of dividends) and they fail to recognize the capital gain that accrues to the equity holders of firms with fixed dollar liabilities in the presence

[7] A closely related explanation, the "variability hypothesis" suggested by Hu and Willett (2000) is that the negative stock return-inflation relation reflects a causal relation between inflation volatility (which is strongly correlated with the level of inflation) and future real activity. Friedman (1977) argues that increased inflation volatility (uncertainty) makes it difficult to extract signals about relative prices from absolute prices; therefore creates economic inefficiency and depressing future economic activity. The "variability hypothesis" is supported by Hu and Willet (2000) but rejected by Buono (1989).

of inflation. Empirical evidence of money illusion is provided by Ritter and Warr (2002)[8] and Campbell and Vuolteenaho (2004)[9]. Also, in a related literature, Thorbecke (1997), Bomfim (2003), Bernanke and Kuttner (2005) and Rigobon and Sack (2004) find a significant response of stock prices to changes in monetary policy. According to Rigobon and Sack (2004), a 25 basis point increase in the three-month interest rate results in a 1.7% decline in the S&P 500 index and a 2.4% decline in the Nasdaq index.

Recently, Campbell and Vuolteenaho (2004) decomposed the dividend yield into a term due to rationally expected long-run dividend growth, a term due to the subjective risk premium on the market, and a residual term that they attribute to a deviation of subjectively expected dividend growth from objectively expected growth. They used a VAR system to construct empirical estimates of these three components and find that high inflation is positively correlated with rationally expected long-run real dividend growth; thus the negative effect of inflation on stock prices cannot be explained through this channel. Campbell and Vuolteenaho (2004) find that inflation is almost uncorrelated with the subjective risk premium and highly correlated with mispricing[10], supporting the Modigliani-Cohn (1979) view that investors form subjective growth forecasts by extrapolating past nominal growth rates without adjusting for changes in inflation. However, the authors recognize the possibility that that some part of what they call mispricing is in fact a second component of the subjective risk premium, one that is common to all stocks and does not appear in their cross-sectional measure of risk

Thus, the negative stock return-inflation relation can also reflect changes in the expected return and risk aversion. Blanchard (1993), Jagannathan, McGrattan, and Scherbina (2001) and Fama and French (2002), among others,[11] interpret the bull market beginning in 1982 as partly due a falling equity risk premium. Sharpe (2002) examines the effect of inflation forecasts on required (long-run) real stock returns over the period 1983-2001 and finds that this effect is substantial. In his model, the log earnings-price ratio is expressed as a linear function of expected

[8] Ritter and Warr (2000) produce cross-sectional evidence in support of their money-illusion hypothesis. In cross-sectional regressions, they find that the amount of undervaluation is positively correlated with leverage and expected inflation.

[9] The persistent use of the "Fed model" by Wall Street which relates the yield on stocks to the yield on nominal Treasury bonds testifies the money illusion of practitioners (see Asness, 2003).

[10] The authors use smoothed past inflation as a simple proxy for this expectation in their implementation. Their empirical estimates suggest that past smoothed inflation explains nearly 80% of the time-series variation in the aggregate stock market's mispricing.

[11] See e.g. Arnott and Bernstein (2002), Arnott and Ryan (2001), Claus and Thomas (2001), Heaton and Lucas (1999).

inflation, expected future returns, expected earnings growth rates, and the log of the current dividend/payout ratio. Investors expectations (future earnings growth and inflation) are drawn from surveys of professional forecasters. The negative relation between equity valuations and expected inflation is found to be the result of two effects: (i) lower expected real earnings growth (as cited above) and (ii) higher required real returns. A one percentage point increase in expected inflation is estimated to raise required real stock returns about one percentage point, which on average would imply a 20 percent decline in stock prices[12]. Also, Blanchard (1993) finds that the expected equity premium has experienced a long decline since the 1950s from unusually high level in the late 1930s and 1940s. Blanchard examines the importance of inflation expectations and attributes some of the recent trend to a decline in expected inflation.

Finally, Feldstein (1980) argued that much of inflation's negative valuation effect could be explained by basic features of the current US tax laws, particularly historic cost depreciation and the taxation of nominal capital gains. However, the empirical evidence of the negative stock-return relation is also provided at international level and as noted by Ritter and Warr (2002), in 1981, partly in response to high inflation, the US tax code was changed to accelerate depreciation, reducing the distortions.

3. Estimating the long-term relationship between stock prices and inflation

The present value model assumes that prices depend upon the present value of discounted future dividends, where the discount rate is equivalent to the required rate of return. In our empirical implementation we use the loglinear version of the present value model proposed by Campbell and Shiller (1988). In the loglinear dynamic valuation framework of Campbell and Shiller, the log dividend-price ratio can be written as:

$$d_t - p_t = -\frac{\kappa}{1-\rho} + E_t\left[\sum_{j=0}^{\infty} \rho^j r_{t+j} - \sum_{j=0}^{\infty} \rho^j \Delta d_{t+j}\right], \qquad (1)$$

[12] But the inflation factor in expected real stock returns is also in long-term Treasury yields; consequently, expected inflation has little effect on the long-run equity premium.

where E_t denotes investors expectations taken at time t, Δd_{t+j} denotes dividend growth in *t+j*, calculated as the change in the log of real dividends per share, and r_{t+j} denotes log stock return during period *t+j*. The expected return equals the real risk-free interest rate plus a risk premium. ρ and κ are parameters of linearization defined by $\rho \equiv 1/(1+\exp(\overline{d-p})$ and $\kappa \equiv -\log(\rho)-(1-\rho)\log(1/\rho-1)$. Equation 1 states that expected stock returns and dividend growth can be predicted by the log dividend-price ratio.

Following Nelson (1999) and Sharpe (2002), we decompose the log dividends per share into the sum of the log earnings per share and the payout ratio. Then, the Campbell-Shiller formula can be rewritten as:

$$e_t - p_t = -\frac{\kappa}{1-\rho} + E_t\left[\sum_{j=0}^{\infty}\rho^j\, r_{t+j} - \sum_{j=0}^{\infty}\rho^j\,\Delta e_{t+j} - (1-\rho)\sum_{j=0}^{\infty}\rho^j\,(d_{t+j}-e_{t+j})\right], \qquad (2)$$

where $e_t - p_t$ denotes the log earning-price ratio, Δe_{t+j} denotes real earning growth in *t+j*, calculated as the change in the log of real earnings per share, and $d_{t+j} - e_{t+j}$ denotes the log of the payout ratio (dividends/earnings) in *t+j*.

This reformulation enable us to focus on earnings which are more closely related to economic fundamentals than dividends since they can be affected by shifts in corporate financial policy. Campbell (2000) argues that dividends creates several difficulties for empirical work. First, many companies pay cash to shareholders partly by repurchasing shares on the open market (for fiscal reasons) which biased the dividend yield (see Liang and Sharpe, 1999). Second, many companies seem to be postponing the payment of dividends until much later in their life cycle. Fama and French (2001) observe that the proportion of listed US companies paying cash dividends falls from 66.5% in 1978 to 20.8% in 1999.

In Equation (2), if $e_t - p_t$ is non-stationary, the right hand-side is also non-stationary and possibly reflects the use of a nominal discount rate, b_t, by investors or a time-varying risk premium which can be expressed as a linear function of the expected inflation, π_t^e. It is generally agreed, see Stock and Watson (1988, 2003), that interest rates and inflation series are I(1) variables.

Under the preliminary assumptions (verified after), that $d_{t+j} - e_{t+j}$ and Δe_{t+j} are stationary and $e_t - p_t$, b_t and π_t^e are I(1) processes, we investigate the cointegration relationships between $e_t - p_t$ and b_t, and between $e_t - p_t$ and π_t^e. Then, these presumed cointegrating relationships imply that a deviation from the long-run equilibrium impacts positively or negatively the (log) earning-price ratio such that the equilibrium is restored. Indeed, these potential relationships could not be expected to hold exactly and deviations may arise due to bubbles, noise trading, fads, and omission of other relevant variables.

The first step in our analysis is to document the negative relations between real stock prices and various measures of inflation. We use five different methods of computing expected inflation[13]. First, under the assumption that investors possess perfect foresight, expected inflation will be equal to realized inflation (π_t). The second method uses once-lagged inflation as the forecast (π_{t-1}). In the third method, expected inflation is derived from an ARIMA model (π_t^{ari}). In the fourth method, following Lee (1992) and Zhong, Darrat and Anderson (2003), expected inflation is modeled rationally as $\pi_t^{kal} = E_{t-1}\left[\pi_t \middle| \pi_{t-1}, MB_{t-1}, b_{t-1}, IP_{t-1}\right]$ by using a simple Kalman Filter (updating) method, where MB_t is the growth rate of the monetary base, b_t is the three-month treasury bill rate, and IP_t is the growth rate of the industrial production average. In the fifth method, following Cozier and Rahman (1988), expected inflation is based on a forecasting model that includes lagged values of the variables used in your fourth method (π_t^{ols}).

We use quarterly data over the post-World War II period (1948:1–2004:1). The quarterly Standard & Poor's (S&P) nominal stock prices, dividends, and earnings indexes are from Campbell and Shiller (1998), which begin in 1926 and extend to 2004[14]. We deflate the three nominal indexes using the consumer price index (all urban consumers) from the Bureau of Labor Statistics (BLS) in order to obtain series for real stock prices, real dividends, and real earnings. The monetary base, the T-bill rate and the growth rate of the industrial production average are available from the FRED II database of the Federal Reserve Bank of St. Louis[15].

[13] Fama and Schwert (1977), Geske and Roll (1983) and others use the contemporaneous nominal treasury bill rate as a proxy for expected inflation. We do not use this method because it will be equivalent to test the nominal discount rate hypothesis

[14] The S&P 500 data are available from Robert Shiller's home page at http://www.econ.yale.edu/~shiller. The complete documentation for the data sources is also provided here. Data are updated from the standard and poor's web site (S&P 500 Earnings and Estimate Report).

[15] Available at http://research.stlouisfed.org/fred2/

The non-stationarity is not rejected for the earning-price ratio, the T-bill rate and inflation in levels, but the hypothesis is rejected if the variables are expressed in first-differences (see Table A1 in appendix). Thus, it is possible that the earning-price ratio is cointegrated with our measures of expected inflation and the nominal risk free rate.

Therefore, we test for cointegration using two distinct methodologies, namely the multivariate trace statistic developed by Phillips and Ouliaris (1990), and the Johansen and Juselius (1992) approach (Trace Test). Table 1 displays tests results. The only deterministic components in the models are the intercept in the cointegration space. The appropriate lag-length is selected in order to accept the assumption that residuals are white noise based on LM(1) and LM(4) criteria. As table 1 shows, there is sufficient evidence for one non-zero co-integrating vectors between $e_t - p_t$ and π_t , π_{t-1} or π_t^{ari}. On the other hand, the hypothesis of no cointegration between $e_t - p_t$ and b_t can not be rejected at conventional significance level. The cointegration evidence between $e_t - p_t$ and π_t^{kal} or π_t^{ols} is mixed depending on the implemented test. For all that, in the remainder of the paper, we focus on realized inflation rather than expected inflation because we intend to provide evidence of the in-sample and out-of sample predictability of stock returns from past information.

The long-term relationship between $e_t - p_t$ and π_t^e implies that a deviation from the long-run equilibrium impacts positively or negatively the (log) earning-price ratio such that the equilibrium is restored. Now, we would like investigate if these deviations have an impact on the real stock prices, real earnings or both. We estimate a vector error correction model (VECM) for real stock prices, real earnings and inflation with restrictions on the cointegrating vector. We constrained the long-run parameters such as the cointegration vector in the VECM is similar to that obtained previously in the cointegration relationship between the earning-price ratio and inflation. Table 2 presents results of the constrained VECM[16]. The table reveals some interesting points. First, real earning growth is somewhat predictable by their own lags, by lags of real stock prices growth and by inflation growth with 6 lags[17]. Second, the error correction term predicts real stock prices growth but it doesn't appear at a statistically significant level in the equations for real earnings. Also, the magnitude of the coefficient on the error correction term in the inflation growth equation is substantially smaller than in the real stock prices equation. These results

[16] The results of the non-constrained VECM are qualitatively the same.
[17] In a VECM with more lags, lags of inflation growth longer than six does not appear significant.

suggest that the empirical evidence of the "proxy hypothesis" is weak and especially that deviations from the shared trend in log earning-price ratio and inflation are better described as transitory movements in real stock prices than as transitory movements in real earnings or inflation.

The next step in our analysis is to investigate the role of these transitory movements in real stock prices in forecasting stock returns. Before that, it is necessary to obtain consistent estimates of the parameters of the shared trend in log earning-price ratio and inflation. Following Lettau and Ludvigson (2001), we use the dynamic ordinary least squares (DOLS) developed by Stock and Watson (1993) to estimate the cointegration parameters. Specifically, the DOLS estimates the long-run relation directly by OLS augmented by the first difference of the explanatory variables together with their lags and leads (*l*) to eliminate the effects of regressor endogeneity on the distribution of the least squares estimator. Formally, DOLS amounts to running an OLS on the following specification (in the case of the earning-price inflation relation):

$$e_t - p_t = \alpha_1 + \alpha_2\,\pi_t + \sum_{i=-l}^{l} \beta_i \Delta\pi_{t-i} + \varepsilon_t \tag{3}$$

where the AIC and BIC criteria are used to determine the appropriate lead/lag length, with a maximum of 8 lags considered. Equations (4) and (5) report the DOLS estimates (ignoring coefficient estimates on the first differences) respectively for the parameters of the shared trend among earning-price ratio and inflation and the shared trend among earning-price ratio and nominal T-bill rate using data from the fourth quarter of 1951 to the second quarter of 2003[18]:

$$e_t - p_t = \underset{(-35.67)}{-\,3.11} \; \underset{(6.59)}{+10.00}\;\pi_t\,, \tag{4}$$

$$e_t - p_t = \underset{(-26.69)}{-\,3.19} \; \underset{(4.74)}{+8.45}\;b_t\,, \tag{5}$$

where the corrected t-statistics appear in parentheses below the coefficient estimates. We also estimated equation (5), even if no cointegration between earning-price ratio and the T-bill rate

[18] We used the same sample as Lettau and Ludvigson (2004a,b) in order to compare our results with theirs.

can not be rejected, in order to evaluate the predictive power of the deviations from their relation. The estimated cointegrating coefficients suggest that a one percentage point decrease respectively in actual inflation and the T-bill rate is associated with a 10 percent decline and a 8.45% percent decline in the earning-price ratio and thus in real stock prices.

We denote respectively $e\hat{p}i_t$ and $e\hat{p}b_t$, the deviation of (log) earning-price ratio from its predicted value based on the cointegrating regression (4) and the non-cointegrating relation (5). Before investigate the predictive power of these two variables for the real return on stocks and the excess of the return on stocks, we describe the data and provide summary statistics.

4. Asset returns data and Summary Statistics

The data set consists of quarterly observations from 1951:Q4 to 2003:Q2. Stock prices, dividends per share, and quarterly earnings per share all correspond to the Standard & Poor's (S&P) Composite Index described above. Real data are deflated by the Consumer Price Index (All Urban Consumers) published by the BLS. Let r_t denote the real return on the S&P index. The three month T-bill rate is used to construct the real return on the risk free rate, $r_{f,t}$, and the log excess return ($r_t - r_{f,t}$).

Log price, p_t, is the natural logarithm of the real S&P price level in quarter *t*. Log dividends, d_t, are the natural logarithm of real dividends per share in quarter *t*. Log earnings, e_t, are the natural logarithm of real earnings per share in quarter *t*. Following Lamont (1998), the log dividend payout ratio is $d_t - e_t$. The stochastically detrended risk-free rate, $rrel_t$, is the T-bill rate minus its last four-quarter average. This relative bill rate is used by Campbell (1991) and Hodrick (1992) to forecast stock returns. Following Fama and French (1989) and Campbell (1987), we used the term spread, TRM_t, the difference between the 10-year Treasury bond yield and the 3-month Treasury bond yield, and the default spread, DEF_t, the difference between the BAA and AAA corporate bond yields[19]. Following Lettau and Ludvigson (2001, 2004a,b), we use the measure of short-term deviations from the long-run cointegration relationship among the natural

[19] Interest rate data come from the FRED II database.

logarithm of consumption (c), labor income (y) and aggregate wealth (a), henceforth $c\hat{a}y_t$ [20]. The aggregate stock market volatility, σ_t, is the variance of the daily stock market return data adjust for the 1987 stock market crash[21]. Guo (2006) finds that a measure of aggregate stock market volatility in conjunction with the consumption-wealth ratio exhibits substantial out-of-sample forecasting power for excess stock market returns.

Table 3 shows basic summary statistics for the real stock return, the excess return and their forecasting variables. Your estimated trend deviation, $e\hat{p}i_t$, is no surprising highly positively correlated with $e_t - p_t$, $d_t - p_t$ and $e\hat{p}b_t$. Correlations with the real return, the excess return, the relative bill rate, the payout ratio, $c\hat{a}y_t$ and the term spread are positive, and negative with the stock market volatility and the default spread. As reported in the previous literature, many of the forecasting variables are highly persistent. The log earning-price inflation ratio does not escape this rule.

Figure 1 plots the log earning-price inflation ratio and the excess return on the S&P Composite Index over the period 1951:Q3-2003:Q2. The figure shows that large swings in $e\hat{p}i_t$ precede large swings in excess returns over the entire sample. However, this pattern does not hold for several episodes as in the mid of the sixties or in the second half of the nineties when the earning-price ratio fells sharply but excess returns remain positive. This suggests that some non-linearities or structural break could occur in the underlying parameters governing this relationship or in the coefficient estimates of the cointegrating relation between the earning-price ratio and

[20] The deviation of (log) aggregate consumption from its predicted value based on a cointegrating regression between (log) consumption, (log) aggregate assets and (log) aggregate labor income. The consumption, net worth, labor income data and the generated variable cay over the period 1951:Q4 to 2003:Q2 are obtained from Sydney Ludvigson at New-York University (http://www.econ.nyu.edu/user/ludvigsons/). The theoretical justification that Lettau and Ludvigson present for the predictive power of this variable is the log-linearized version of the standard budget constraint relating wealth, consumption, and portfolio returns where the unobservable aggregate wealth variable is approximated by aggregate assets and labor income. However, Brennan and Xia (2004) argue that the predictive power of their variable arises from a “look-ahead bias”. Also, Rudd and Whelan (2002) argue that Lettau and Ludvigson use a set of variables that do not belong together in an aggregate budget constraint, thereby testing a cointegrating relationship that is not implied by their theory. Rudd and Whelan cannot reject the hypothesis that cointegration is absent from the data once they employ measures of consumption, assets, and labor income that are jointly consistent with an underlying budget constraint.

[21] The daily Dow Jones index was obtained from www.economagic.com. Following Campbell et al. (2001), Guo (2006) adjust downward realized stock market variance for 1987:Q4 because the 1987 stock market crash has confounding effects on it. They replace the 1987:Q4 observation by the second largest realized stock market variance in the sample. However, our sample is larger than in Guo (2006) and then, the second largest realized stock market variance differs. So, the predictive power of the stock market variance could be different than in the originally study.

inflation. Nevertheless, theses episodes remain specific and transitory, as reflected in the subsequent continue downturn in excess returns at the end of the 1990's.

5. Quarterly Forecasting Regressions

We report in this section the in-sample regression results. Inoue and Kilian (2004) argue that in-sample tests should be preferred because they have greater power than out-of-sample tests (even adjusted for data mining). The predictive regression model takes the form:

$$y_{t+1} = \alpha_0 + \alpha_1 z_t + u_{t+1}, \qquad (6)$$

where y_t is either real stock returns or excess returns to holding stocks from period t - 1 to period t, z_t is a control variable believed to potentially predict future returns and u_{t+1} is a disturbance term.

The predictive ability of z_t is typically assessed by examining the t-statistic corresponding to $\hat{\alpha}_1$, the OLS estimate of α_1, as well as the goodness-of-fit measure, R^2. We estimate the regression (6) by OLS and use Newey-West (1987) adjustment to the standard errors of the coefficients to correct for serial correlation and heteroscedasticity.

Before examine the predictability of both real stock returns and excess returns, we investigate the predictive power of $e\hat{p}i_t$ on future real stock prices growth, Δp_t, real dividend growth, Δd_t, real earning growth, Δe_t, the payout ratio, $d_t - e_t$, and future real returns on the risk free rate, $r_{f,t}$.

We examine two different vector autoregression models (VAR) where the endogenous variables are each regressed on their own lags and to the lagged value of your estimated trend deviation, $e\hat{p}i_t$. In the first VAR, endogenous variables are the real stock price growth, the real dividend growth, the payout ratio and the real return on the risk free rate. In the second VAR, we substitute the real dividend growth by the real earning growth. Table 4 reports the VAR estimates. We focus on the relationship between future endogenous variable and the estimated trend deviation. Table 4 shows that $e\hat{p}i_t$ predicts real stock prices growth, real dividend growth and the payout ratio. The coefficient on $e\hat{p}i_t$ is not significative at a 5% significance level in the equations for the real risk free rate return and earning growth. This result is similar to that obtained previously where the long-term deviations among earning-price ratio and inflation (the error-correction term) does not enter at a statistically significant level in the equation for real earning growth in the VECM framework. On the other hand, $e\hat{p}i_t$ predicts dividend growth[22] and the payout ratio. This suggests that the corporate financial policy could be affected by the transitory deviations from the common trend in earning-price ratio and inflation. These results also suggest more generally that $e\hat{p}i_t$ could forecast real stock returns and excess returns by forecasting both real stock prices and real dividends.

Table 5 reports one-quarter ahead forecasts of both real returns and excess returns of stocks over the riskfree rate. All models include a constant term. The firsts rows of each panel show that the one lag of the dependent variable is a weak predictor of future returns. This model predicts only 2.5% of next quarter's variation in real stock returns and 1.7% of next quarter's excess returns variation. The log earning-price inflation ratio, $e\hat{p}i_t$, is significant and has more explanatory power than the consumption-wealth ratio, $c\hat{a}y_t$, the log earning-price T-bill ratio, $e\hat{p}b_t$, the dividend-price ratio and the earning-price ratio[23]. Regressions of real stock returns and excess returns on one lag of $e\hat{p}i_t$ produce adjusted R^2 of 9.6% and 9.4% respectively. Moreover, the Newey-West corrected t-statistic for $e\hat{p}i_t$ indicates that the coefficient estimate is nonzero with very high probability. These results are not affected by whether the lagged value of the dependant variable is included in the regression as an additional explanatory variable (rows 5 and 20).

These results are robust to alternative specifications in estimating the log earning-price inflation ratio. They are not sensitive to the value of *l* in estimating the DOLS specification, the choice of estimation method or the measure of expected inflation. In appendix, Table A3 reports

[22] Alternative specifications of the VAR indicates that dividend growth is not predictable by the dividend-price ratio or the earning-price ratio. This is in agreement with a large literature that documents the poor predictability of dividend growth by the dividend yield (e.g., Campbell, 1991; Cochrane, 1991; Lewellen, 2004).

[23] Table A2 in appendix shows that these results are robust to different specifications for the normalized stock prices. We also show regressions with the "log dividend-price inflation ratio" as the sole predictive variable. The predictive power of this variable is inferior to that of the log earning-price inflation ratio

that the forecasting results for different specifications of the log earning-price inflation ratio are very similar[24].

In order to compare the forecasting power of $e\hat{p}i_t$ and $c\hat{a}y_t$, we include both in the same regression (rows 8 and 23). These two variables are both significant and regressions produce higher R^2 than in the univariate models. This suggests that $e\hat{p}i_t$ contains information about future asset returns that is not included in $c\hat{a}y_t$.

To check the robustness of our results, we augment the precedent regressions by adding a variety of variables that are useful in predicting future stock returns (row 24 and 9). These include the payout ratio, the term and default spreads on bonds, the relative bill rate and the stock market volatility. These regressions have more explanatory power than the precedent models. However, only the relative bill rate has a significant predictive power among these five supplementary variables. The two trend deviation terms, $c\hat{a}y_t$ and $e\hat{p}i_t$, are still strongly significant.

6. **Out-of-Sample Tests**

Some recent studies (e.g., Bossaerts and Hillion, 1999; Goyal and Welch, 2003, 2004) expressed concern about the apparent predictability of stock returns because while a number of financial variables display significant in-sample predictive ability, they have negligible out-of-sample predictive power. Also, our forecasting results presented above could suffer from a "look-ahead" bias that arises from the fact that the coefficients used to generate $e\hat{p}i_t$ are estimated using the full sample.

To address these issues, we examine, in this section, the out-of-sample predictability of both real stock returns and excess returns by distinguishing two cases. In the first, agents are assumed to know the cointegration parameters of $c\hat{a}y_t$, $e\hat{p}i_t$, $e\hat{p}b_t$, which are estimated using the full sample. In the second case, the cointegration parameters are estimated recursively using only

[24] We experimented with various lead/lag length in estimating the DOLS specification and we used the cointegrating parameters obtained in the previous section based on Johansen's (1988) full information maximum likelihood approach. We also considered the earning-price inflation ratio from the cointegration relationship among the earning-price ratio and one lag of inflation.

information available at the time of forecast. Moreover, we present out-of-sample predictability results using the two-period lagged value of $c\hat{a}y_t$ and $e\hat{p}i_t$ because these variables are available with a one-month delay relative to financial indicators. This scenario gives some idea of how the model would perform if a practitioner, who must rely on real-time data, uses it. Goyal and Welch (2003, 2004) indeed recommend that one should adopt "the perspective of a real-world investor" (who did not have access to ex-post information).

We present two types of comparisons in order to evaluate the out-of-sample predictive power of $e\hat{p}i_t$: nested comparisons and non-nested comparisons. In the nested comparisons, we compare a benchmark "restricted" model with an unrestricted model which include both the explanatory variables of the restricted model and $e\hat{p}i_t$. In the non-nested comparisons, we compare competitive models with different explanatory variables (popular forecasting variables as the dividend-price ratio or $c\hat{a}y_t$ versus $e\hat{p}i_t$).

We use four statistics to compare the out-of-sample performance of our forecasting models: the mean-squared forecasting error (MSE) ratio, the Clark and McCracken's (2001) encompassing test (ENC-NEW), the McCracken's (2004) equal forecast accuracy test (*MSE-F*) and the modified Diebold-Mariano (*MDM*) encompassing test proposed by Harvey, Leybourne and Newbold (1998)[25]. We apply the *ENC-NEW* and *MSE-F* tests for the non-nested comparisons and the *MDM* test for the nested comparisons. We report the MSE ratio in both nested and non-nested comparisons.

The *ENC-NEW* encompassing test, is a modified Harvey, Leybourne, and Newbold (1998) test statistic adapted to address the fact that the limiting distribution of this test statistic is nonnormal when the forecasts are nested under the null[26]. The *ENC-NEW* statistic provides a test of the null hypothesis that the restricted model (which exclude $e\hat{p}i_t$) incorporates all the relevant information about the next quarter's value of the dependent variable, against the alternative

[25] Professor Simon Van Norden is gratefully thanked for providing us the program of the MDM test.

[26] Forecast encompassing is based on optimally constructed composite forecasts. Intuitively, if the forecasts from the restricted regression model encompass the unrestricted model forecasts, the additional variable included in the unrestricted model provides no useful additional information for predicting returns relative to the restricted model which excludes this variable; if the restricted model forecasts do not encompass the unrestricted model forecasts, then the additional variable does contain information useful for predicting returns beyond the information already contained in a model that excludes this variable. Tests for forecast encompassing are similar to testing whether the weight attached to the unrestricted model forecast is zero in an optimal composite forecast composed of the restricted and unrestricted model forecasts.

hypothesis that the unrestricted model (which include $e\hat{p}i_t$) provide additional information that could be used to significantly improve the restricted model's forecast.

The *MSE-F* test is a test of equal MSE. The null hypothesis for this test is that the restricted model has a MSE that is less than or equal to that of the unrestricted model; the alternative is that the unrestricted model has lower MSE. Clark and McCracken (2001) show that these two tests have the best overall power and size properties among a variety of tests proposed in the literature.

The *MDM* test, is a modified Diebold and Mariano (1995) test statistic to test for forecast encompassing between two non-nested models and to account for finite-sample biases. This test statistic is formed by asking whether the difference in forecast errors between two models is correlated with the forecast error of the model that is encompassing under the null. The null hypothesis is that the competitor model 2, without $e\hat{p}i_t$, encompasses model 1 where the predictive variable is $e\hat{p}i_t$.

As in Lettau and Ludvigson (2001), we use the first one-third observations for the initial in-sample estimation and form the out-of-sample forecast recursively in the remaining sample. The initial estimation period begins with the fourth quarter of 1951 and ends with the first quarter of 1968. The model is recursively reestimated until the end the of sample.

Figure 2 plots the recursively estimated coefficient on inflation. The point estimates show large variations until the end of the 1970s because it requires a relatively large number of observations to consistently estimate the cointegration parameters. After a stabilized phase, the inflation coefficient increased progressively during the 1990's, possibly reflecting a higher inflation aversion of investors in a permanent low inflation environment[27]. However, the results presented below indicate that the forecasting ability of $e\hat{p}i_t$ does not deteriorates if the cointegration parameters are estimated recursively relative to the fixed parameters using the full sample.

We report results of the out-of-sample one-quarter-ahead nested forecast comparisons of real stock returns and excess returns in Tables 6 and 7 respectively. We consider two restricted (benchmark) models: a model that includes only a constant as a predictor and a model that

[27] The Andrews-Quandt and Andrews-Ploberger structural break tests (Andrews and Ploberger, 1994; Hansen, 1997) indicate a structural break in the parameter stability in 1989:Q3. The Bai and Perron (2003) test detects also one structural break in 1989:Q3. These results could also reflect the persistent deviation from the common trend in earning-price ratio and inflation that appears in the 1990's.

includes both a constant and the lagged dependent variable as predictive variables. The nested comparisons are made by alternately augmenting the benchmark with either the one-period lagged value of $e\hat{p}i_t$, or the two-period lagged value, denoted $e\hat{p}i_{t-1}$. We present results based on a fixed cointegrating vector where the cointegrating parameters are set equal to their values estimated in the full sample and a recursive reestimated cointegrating vector.

Consistent with the in-sample regression results, we find that the unrestricted model (which include $e\hat{p}i_t$) has smaller MSE than the constant restricted model or the autoregressive restricted model. Tables show that regardless of whether the cointegrating parameters are reestimated, or whether the one- or two-period lagged value of $e\hat{p}i_t$ is used as a predictive variable, both *ENC-NEW* and *MSE-F* tests reject the null hypothesis that $e\hat{p}i_t$ provides no information about future stock returns at the 1% significance level.

Results of the out-of-sample one-quarter-ahead non-nested forecast comparisons of real stock returns and excess returns are shown in Tables 8 and 9 respectively. We compare alternatively the model 1 in which the lagged value of $e\hat{p}i_t$ is the sole predictive variable with "competitor models" in which either the lagged dependent variable, lagged dividend-price ratio, lagged earning-price ratio, lagged dividend payout ratio, lagged detrended bill rate, lagged value of $c\hat{a}y_t$ (with/without the measure of stock market volatility), lagged value of $e\hat{p}b_t$ is the sole predictive variable. A constant is included in each of the forecasting equations.

The results indicate that the $e\hat{p}i_t$ forecasting model produces lower MSE than any of the "competitor" model. Moreover, the *MDM* encompassing test indicates that the model using lagged $e\hat{p}i_t$ contains information that provides superior forecasts to those produced by most of the other models. The findings are statistically significant at better than the two percent level in almost every case, regardless of whether the cointegrating parameters are reestimated[28].

In summary, the results presented indicate that $e\hat{p}i_t$ has displayed statistically significant out-of-sample predictive power for both real stock returns and excess returns over the postwar period, and contains information that is not included in lagged value of the dependent variables or a model of constant expected returns. The non-nested forecasts comparisons results suggest also

[28] Except when the log earning-price inflation ratio is recursively reestimated and the competitor models include the consumption-wealth ratio or the dividend-price ratio. However, in theses cases, The inverse MDM tests that our variable encompasses the competitor models are not rejected with greater p-value.

that forecasts using $e\hat{p}i_t$ would be consistently superior to forecasts using any other popular forecasting variables.

7. Long-horizon Forecasts

In this section, we investigate the relative predictive power of the log earning-price inflation ratio for long-horizon stock returns. The relatively modest absolute value of the coefficient on the error-correction term in the VECM framework presented above and the graphical evidence of persistent deviations from the common trend in earning-price ratio and inflation (see Figure 1) both suggest that $e\hat{p}i_t$ should provide useful information for predicting stock returns at intermediate horizons.

We use two different methodologies in order to evaluate the long-horizon predictability of stock returns. The first consists of single-equation regressions as in Lettau and Ludvigson (2001) that provide a simple way to summarize the marginal predictive power of each forecasting variable and the overall explanatory power of the forecasting equations. The second consists of the two out-of-sample tests for nested forecasts models presented above: the encompassing ENC-NEW test and the equal forecast accuracy *MSE-F* test. Since these remaining tests have nonstandard limiting distributions that are usually dependent upon unknown nuisance parameters, we follow Clark and McCracken (2004) in using a bootstrap procedure similar to that in Kilian (1999) to estimate asymptotically valid critical values and construct asymptotically valid p-values[29]. Following Rapach et Wohar (2004b), we use a restricted (benchmark) model of constant returns for long-horizon forecasts.

The *k*-period dependent variable, $y_{k,t+k}$, in these long-horizon regressions is measured by $y_{k,t+k} = \sum_{i=1}^{k} y_{t+i}$. We consider horizons of 1 to 24 quarters and a very long horizon of 48 quarters.

Before presenting results from long-horizon regressions of real stock returns and excess returns, we report in Table 10 results of single-equation regressions of stock prices growth, dividend growth and earning growth at long-horizons. Theses results confirm findings presented

[29] The bootstrap procedure is briefly described in appendix and in more details in Clark and McCracken (2004).

in Table 5 that $e\hat{p}i_t$ predicts stock prices growth and dividend growth but has no predicting power for earning growth. The predictive power of $e\hat{p}i_t$ increases with *k* until it reaches a peak around 2-3 years. Beyond this peak, it decreases progressively until a horizon of 6 years.

On the contrary, the dividend-price ratio and earning-price ratio display no forecasting power for any dependent variables at short and intermediate horizons except for dividend growth with the dividend-price ratio at horizons of 12 and 16 quarters (row 5). The valuation ratios become significant at very long horizons but the predictive power of the dividend-price ratio and the earning-price ratio, for which we do not reject the non-stationary, probably suffer from a spurious regression problem. Overlapping observations (when $k > 1$) are not independent and that induces serial correlation in the disturbance term (Richardson and Stock, 1989). Even when robust standard errors are used to compute t-statistics (using the Newey-West procedure), in finite samples, there is a strong tendency for the t-statistic to increase in absolute value, as the overlap increases, whether or not there is a relationship between the variables (e.g. Hodrick, 1992; Nelson and Kim, 1993; Goetzmann and Jorion, 1993) [30].

Tables 11 and 12 present results of long-horizon regressions of both real stock returns and excess returns at horizons ranging from 1 to 48 quarters. First rows of these tables show that $e\hat{p}i_t$ has statistically significant forecasting power for both real stock returns and excess returns at long horizons. Moreover, the forecasting power of $e\hat{p}i_t$ is in the most of cases superior of any other predictive variable at horizons ranging from 1 to 12 quarters (rows 1 to 6). As in the precedent long-run regressions, the predictive power of $e\hat{p}i_t$ increases with horizon until a horizon of 3 years after that it progressively decreases. When we include $e\hat{p}i_t$, $c\hat{a}y_t$, the payout ratio, the stochastically detrended short rate, the term spread and the default spread together in one regression (rows 7), R^2 statistics are higher at horizons ranging from 1 to 12 quarters than in regressions where the dividend-price ratio or $e\hat{p}b_t$ replaces $e\hat{p}i_t$ (rows 8 and 9).

Figure 3 plots realized and predicted excess returns by the univariate model with $e\hat{p}i_t$ as the sole predictor (row 2) for different horizons. It provides a simple way to visualize the

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30 As noted by Valkanov (2003), overlapping a non-trivial fraction of the sample produces a persistent variable that behaves very much like a I(1) process. Indeed, at these very long horizons, we can not reject a unit root process at a 5% level in the dependent variables (ADF test). Ferson et. al. (2003) provide simulation evidence that predictors with large autocorrelation coefficients suffer from a spurious regression problem if the true process for the dependent variable is also persistent.

information about future excess returns that $e\hat{p}i_t$ contains at different horizons. The figure shows the improvement in the ability of the log earning-price inflation ratio to forecast future excess returns as the horizon increases until k = 12 and then the progressively decrease in the predictive power of $e\hat{p}i_t$.

Table 13 presents *MSE-F* and *ENC-NEW* out-of-sample statistics of both real stock returns and excess returns at horizons ranging from 1 to 48 quarters. The p-values are generated using the bootstrap procedure described in appendix. As in the precedent section, we present results based on a fixed cointegrating vector and a recursive reestimated cointegrating vector. The table shows that the unrestricted model (which include $e\hat{p}i_t$) has smaller MSE than the constant restricted model at horizons less than 6 years.

Regardless of whether the cointegrating parameters are reestimated, the *ENC-NEW* and *MSE-F* tests reject the null hypothesis that $e\hat{p}i_t$ provides no information about future excess returns at the 5% significance level for horizons of 1 to 16 quarters. The *ENC-NEW* and *MSE-F* tests reject the null that $e\hat{p}i_t$ has no predictive power at the 5% significance level for future real stock returns at horizons less than 4 years except the *ENC-NEW* when the cointegrating vector is reestimated at horizons of 8 and 12 quarters. In these two last cases, we reject the null at the 10% level.

8. Summary and conclusion

The observed negative relationship between stock prices/stock returns and both expected and realized inflation during the post-World War II period is “troublesome” because it appears to contradict the Fisher Hypothesis, which states that expected stock returns move one-for-one with expected inflation since stocks are claims on “physical” or real assets. The inflation-stock return/stock prices correlation has been subjected to extensive study since a quarter century. However, there is less consensus on what drives this negative relation.

In this article, we consider a new perspective on the relationship between stock prices and inflation, by estimating the common long-term trend in real stock prices, as reflected in the earning-price ratio, and both expected and realized inflation. We estimated a VECM, based on a variant of the Campbell-Shiller price-dividend model, for real stock prices, real earnings and realized inflation where we constrained the long-run parameters such as the cointegration vector in the VECM is similar to that obtained previously in the cointegration relationship between earning-price ratio and inflation. The results of the constrained VECM suggest that the empirical evidence of the "proxy hypothesis" is weak and especially that deviations from the shared trend in real stock prices, real earnings and inflation are better described as transitory movements in real stock prices than as transitory movements in real earnings or inflation. This implies that a deviation from the long-run equilibrium impacts positively or negatively stock prices such that the equilibrium is restored.

We investigate the role of these transitory deviations from the common trend in the earning-price ratio and inflation for forecasting stock returns. We find that the log earning-price inflation ratio predicts real stock prices growth, real dividend growth and the payout ratio while it does not predict – consistent with the VECM results – real earning growth. This suggests that the corporate financial policy could be affected by the transitory deviations from the common trend in earning-price ratio and inflation. These results also suggest more generally that the log earning-price inflation ratio could forecast real stock returns and excess returns by forecasting both real stock prices and real dividends.

Indeed, we find that the trend deviations from the share trend in the earning-price ratio and inflation exhibit substantial in-sample and out-of-sample forecasting abilities for both real stock returns and excess returns. Moreover, we find that these trend deviations provide information about future stock returns that is not captured by other popular forecasting variables over short and intermediate horizons (from 1 to 12 quarters) and that the log earning-price inflation ratio is the best univariate predictor of stock returns over theses horizons.

Also, our results do not support the hypothesis of Modigliani and Cohn's inflation illusion that states that investors use a nominal rate to discount real cash flows. First, we can not reject the hypothesis of no cointegration between the earning-price ratio and the nominal risk free rate over our sample, whereas there is sufficient evidence for one non-zero co-integrating vectors between the earning-price ratio and expected inflation/realized inflation. Second, the predictive power of the log earning-price T-bill ratio is always inferior to that of the log earning-price inflation ratio.

In this article, we examined the forecasting ability of the log earning-price ratio through a linear regression method. However, as shown in Figure 1, there are several episodes, as in the mid of the sixties and in the second half of the nineties, where the earning-price ratio fells sharply but excess returns remain positive. Also, some recent works (e.g. Coakley and Fuertes, 2003; Bohl and Siklos, 2004; Ma and Kanas, 2004) documenting non-linearities in the U.S. stock market valuation ratios. These suggest that an extension of our work would be to investigate whether a non-linear model can improve forecasts of stock returns.

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Table 1. Phillips-Ouliaris and Johansen Cointegration Tests

Z_t	P-O Trace Test			Johansen Trace Test						
	Test Stat.	90% CV	95% CV	# of coint. relation	Test Stat.	90% CV	95% CV	lags	LM(1)	LM(4)
$\left[ep_t, \pi_t\right]$	**60.05**	47.59	55.22	0	**23.29**	17.79	19.99	6	5.19	7.78
				1	3.98	7.50	9.13		(p=0.27)	(p=0.10)
$\left[ep_t, \pi_{t-1}\right]$	**61.71**	47.59	55.22	0	**20.84**	17.79	19.99	4	4.17	9.16
				1	4.53	7.50	9.13		(p=0.38)	(p=0.06)
$\left[ep_t, \pi_t^{kal}\right]$	**55.57**	47.59	55.22	0	11.58	17.79	19.99	4	5.69	3.31
				1	5.59	7.50	9.13		(p=0.22)	(p=0.51)
$\left[ep_t, \pi_t^{arima}\right]$	**69.36**	47.59	55.22	0	**22.85**	17.79	19.99	6	4.31	7.87
				1	2.99	7.50	9.13		(p=0.37)	(p=0.10)
$\left[ep_t, \pi_t^{ols}\right]$	**67.77**	47.59	55.22	0	11.72	17.79	19.99	13	4.59	5.08
				1	1.96	7.50	9.13		(p=0.33)	(p=0.28)
$\left[ep_t, tb_t\right]$	33.61	47.59	55.22	0	17.20	17.79	19.99	3	2.40	3.27
				1	5.29	7.50	9.13		(p=0.66)	(p=0.51)

Note: The table reports tests of the null hypothesis of no cointegrating relationships against the alternative of one or more cointegrating vectors. “Lags” gives the number of lags in the estimated VAR model. The appropriate lag-length is selected in order to accept the assumption that residuals are white noise based on LM(1) and LM(4) criteria. A test statistic greater than the specified critical value suggests rejection of the null of no cointegration. Significant coefficients at the 5% level are highlighted in bold face.

Table 2. Estimated constrained VECM

	i	Δp_t	Δe_t	$\Delta \pi_t$
Δp_{t-i}	1	0.11	**0.09**	-0.01
	2	-0.04	0.06	0.00
	3	-0.01	-0.01	0.01
	4	0.00	0.00	0.00
	5	-0.04	0.02	0.01
	6	-0.01	**-0.10**	**-0.02**
Δe_{t-i}	1	-0.10	**0.69**	0.01
	2	0.04	0.07	0.01
	3	-0.05	-0.03	0.00
	4	0.15	**-0.44**	0.01
	5	0.05	**0.43**	-0.03
	6	-0.09	**-0.16**	0.03
$\Delta \pi_{t-i}$	1	-0.48	0.35	**0.25**
	2	0.69	0.07	0.11
	3	**-1.74**	-0.15	**0.28**
	4	1.05	-0.52	**-0.32**
	5	0.11	0.29	-0.04
	6	0.23	**-0.75**	-0.02
$\text{-}\,e\hat{p}i_{t-i}$	1	**-0.04**	0.00	**-0.00**
$\text{-}\,e\hat{p}i_t = p_t - e_t + 18.92\pi_t - 3.52$				

Note: The sample period is firth quarter of 1948 to firth quarter 2004. Significant coefficients at the 5% level are highlighted in bold face.

Table 3. Summary statistics

Correlation Matrix												
	r_t	$r_t - r_{f,t}$	$e_t - p_t$	$d_t - p_t$	$d_t - e_t$	$RREL_t$	DEF_t	TRM_t	σ_t	$c\hat{a}y_t$	$e\hat{p}i_t$	$e\hat{p}b_t$
r_t	1,00	0,15	0,23	0,26	0,05	-0,21	0,10	0,10	0,00	0,31	0,33	0,29
$r_t - r_{f,t}$		1,00	0,21	0,25	0,07	-0,20	0,11	0,14	0,11	0,31	0,32	0,32
$e_t - p_t$			1,00	0,90	-0,28	0,08	0,38	-0,19	-0,13	0,25	0,69	0,79
$d_t - p_t$				1,00	0,18	0,01	0,34	-0,03	-0,24	0,36	0,73	0,82
$d_t - e_t$					1,00	-0,16	-0,10	0,37	-0,23	0,23	0,05	0,01
$RREL_t$						1,00	-0,28	-0,23	-0,19	-0,16	0,06	0,09
DEF_t							1,00	0,28	0,27	0,06	-0,03	0,03
TRM_t								1,00	0,04	0,32	0,00	-0,02
σ_t									1,00	-0,06	-0,31	-0,23
$c\hat{a}y_t$										1,00	0,28	0,30
$e\hat{p}i_t$											1,00	0,83
$e\hat{p}b_t$												1,00
Univariate Summary Statistics												
Mean	0.05	0.04	-2.73	-3.43	-0.70	0.00	0.01	0.01	0.00	0.00	0.00	0.01
SD	0.08	0.07	0.39	0.39	0.18	0.01	0.00	0.01	0.00	0.01	0.32	0.34
Max	0.28	0.29	-1.92	-2.78	-0.27	0.05	0.03	0.04	0.00	0.03	0.83	0.82
Min	-0.23	-0.23	-3.84	-4.50	-1.19	-0.04	0.00	-0.03	0.00	-0.04	-0.88	-0.81
Autoc.	0.16	0.15	0.97	0.95	0.96	0.51	0.91	0.80	0.51	0.83	0.96	0.95

Note: The sample spans the fourth quarter of 1951 to the second quarter of 2003 except for the term spread, TRM_t, which begin the second quarter of 1953.

Table 4. Estimates of the VAR models

	Equation 1				Equation 2			
Endogenous variable	Δp_t	Δd_t	$d_t - e_t$	$r_{f,t}$	Δp_t	Δe_t	$d_t - e_t$	$r_{f,t}$
$e\hat{p}i_{t-1}$	**0.055**	**0.008**	**0.026**	0.006	**0.053**	-0.015	**0.026**	0.002
(p-value)	(0.001)	(0.009)	(0.004)	(0.224)	(0.002)	(0.064)	(0.003)	(0.448)
$\overline{R}^2$	0.04	0.17	0.95	0.73	0.05	0.48	0.95	0.71
	LAG =2				LAG =1			

Both AIC and SIC are used to select the lag length. Estimated coefficients of the endogenous variables are not shown. Significant coefficients at the 5% level are highlighted in bold face.

Table 5. Forecasting Quarterly Excess Returns

#	Constant (*t*-stat)	*lag* (t-stat)	$c\hat{a}y_t$ (*t*-stat)	$e\hat{p}i_t$ (*t*-stat)	$e\hat{p}b_t$ (*t*-stat)	σ_t (*t*-stat)	$d_t - p_t$ (*t*-stat)	$e_t - p_t$ (*t*-stat)	$d_t - e_t$ (*t*-stat)	$RREL_t$ (*t*-stat)	TRM_t (*t*-stat)	DEF_t (*t*-stat)	$\overline{R}^2$
						Panel A: Excess Returns							
1	**0.037** (6.520)	**0.147** (2.171)											0.017
2	**0.044** (8.515)		**1.813** (4.460)										0.086
3	**0.041** (8.184)	0.059 (0.939)	**1.702** (4.371)										0.084
4	**0.043** (8.669)			**0.072** (4.418)									0.094
5	**0.041** (7.595)	0.054 (0.853)		**0.068** (4.153)									0.092
6	**0.042** (8.163)				**0.065** (3.981)								0.083
7	**0.039** (6.921)	0.060 (0.887)			**0.061** (3.670)								0.082
8	**0.044** (9.526)		**1.401** (3.495)	**0.057** (3.708)									0.139
9♦	0.035 (1.657)		**1.181** (2.939	**0.075** (4.700		87.137 (1.199)			-0.003 (-0.092)	**-1.170** (-2.607	0.170 (0.159)	-0.116 (-0.267)	0.166
10	**0.034** (5.265)		**1.298** (3.334)	**0.069** (4.474)		114.880 (1.609)				-0.614 (-1.561)			0.152
11	**0.130** (3.127)		**1.558** (3.629)					**0.032** (2.113)					0.107
12	**0.158** (2.814)		**1.436** (3.312)				**0.034** (2.034)						0.108
13	**0.213** (4.011)						**0.050** (3.181)						0.063
14	**0.164** (3.957)							**0.044** (2.977)					0.049
15♦♦	**0.043** (8.389)			**0.061** (3.922)									0.085
						Panel B: Real Returns							
16	**0.039** (6.633)	**0.158** (2.254)											0.025
17	**0.047** (8.889)		**1.868** (4.469)										0.089
18	**0.044** (8.440)	0.068 (1.020)	**1.737** (4.332)										0.089
19	**0.046** (9.022)			**0.074** (4.381)									0.096
20	**0.043** (7.537)	0.063 (0.974)		**0.069** (4.164)									0.096
21	**0.046** (8.310)				**0.061** (3.583)								0.071
22	**0.042** (6.781)	0.085 (1.188)			**0.055** (3.298)								0.073
23	**0.047** (9.958)		**1.446** (3.449)	**0.059** (3.650)									0.144
24♦	0.034 (1.536)		**1.201** (2.948)	**0.076** (4.721)		71.131 (0.968)			-0.006 (-0.184)	**-1.227** (-2.752)	0.501 (0.473)	-0.073 (-0.170)	0.175
26	**0.132** (2.999)		**1.619** (3.618)					0.031 (1.964)					0.109
27	**0.157** (2.676)		**1.504** (3.306)				0.032 (1.876)						0.109
28	**0.166** (3.907)							**0.044** (2.886)					0.047
29	**0.215** (3.949)						**0.049** (3.078)						0.060
30♦♦	**0.046** (8.703)			**0.062** (3.830)									0.085

Note: The table reports estimates from OLS regressions of stock returns on lagged variables named at the head of a column. Regressions use data from the fourth quarter of 1951 to the second quarter of 2003, except for regression 13 and 24 (indicated by ♦), which begins in the second quarter of 1953, the largest common sample for which all the data are available. Rows 15 and 30 (indicated by ♦♦) report estimates with the log dividend-price inflation ratio as regressor. Newey-West corrected t-statistics appear in parentheses below the coefficient estimate. Significant coefficients at the 5% level are highlighted in bold face.

Table 6. One-Quarter-Ahead Forecasts of Excess Returns: Nested Comparisons

Row	Comparison unrestricted vs. restricted	MSE_u/MSE_r	*ENC-NEW* Statistic	*ENC-NEW* 99 percent CV	*MSE-F* Statistic	*MSE-F* 99 percent CV
		Panel A: Cointegrating Vector Reestimated				
1	$\hat{epi}_t$ vs. *AR*	0.9392	9.066**	4.251	9.339**	3.970
2	$\hat{epi}_{t-1}$ vs. *AR*	0.9472	7.998**	4.251	8.068**	3.970
3	$\hat{epi}_t$ vs. *const*	0.9264	11.621**	4.251	11.129**	3.970
4	$\hat{epi}_{t-1}$ vs. *const*	0.9344	10.562**	4.251	9.793**	3.970
		Panel B: Fixed Cointegrating Vector				
5	$\hat{epi}_t$ vs. *AR*	0.9328	12.889**	4.251	10.227**	3.970
6	$\hat{epi}_{t-1}$ vs. *AR*	0.9472	10.020**	4.251	7.908**	3.970
7	$\hat{epi}_t$ vs. *const*	0.9216	16.266**	4.251	12.004**	3.970
8	$\hat{epi}_{t-1}$ vs. *const*	0.9376	13.213**	4.251	9.418**	3.970

Note: The *MSE-F* statistic is used to test the null hypothesis that the MSE for the unrestricted model forecasts is less than or equal to the MSE for the restricted model forecasts. The *ENC-NEW* statistic is used to test the null hypothesis that restricted model forecasts encompass the unrestricted model forecasts. We estimate the cointegration parameters recursively in panel A and using the full sample in panel B. We consider a restricted (benchmark) model of autoregressive returns (*AR*) in rows 1,2,5 and 6. A restricted (benchmark) model of constant returns (*const*) is considered in rows 3,4,7 and 8. Each of these model includes a constant. MSE_u is the mean-squared forecasting error from the relevant unrestricted model in each row; MSE_r is the mean-squared error from the relevant restricted model. A number less than one indicates that the unrestricted model has lower forecasting error than the restricted model. The initial estimation period begins with the fourth quarter of 1953 and ends with the first quarter of 1968. The model is recursively reestimated until the second quarter of 2003. A * (**) denotes significance at the five (one) percent level.

Table 7. One-Quarter-Ahead Forecasts of Real Returns: Nested Comparisons

Row	Comparison unrestricted vs. restricted	MSE_u/MSE_r	*ENC-NEW* Statistic	*ENC-NEW* 99 percent CV	*MSE-F* Statistic	*MSE-F* 99 percent CV
Panel A: Cointegrating Vector Reestimated						
1	$\hat{epi}_t$ vs. *AR*	0.943	8.406**	4.251	8.665**	3.970
2	$\hat{epi}_{t-1}$ vs. *AR*	0.950	7.430**	4.251	7.541**	3.970
3	$\hat{epi}_t$ vs. *const*	0.930	11.141**	4.251	10.668**	3.970
4	$\hat{epi}_{t-1}$ vs. *const*	0.938	10.192**	4.251	9.500**	3.970
Panel B: Fixed Cointegrating Vector						
1	$\hat{epi}_t$ vs. *AR*	0.931	13.027**	4.251	10.706**	3.970
2	$\hat{epi}_{t-1}$ vs. *AR*	0.945	10.075**	4.251	8.380**	3.970
3	$\hat{epi}_t$ vs. *const*	0.916	16.938**	4.251	12.888**	3.970
4	$\hat{epi}_{t-1}$ vs. *const*	0.933	13.745**	4.251	10.248**	3.970

Note: See Table 6.

Table 8. One-Quarter-Ahead Forecasts of Excess Returns: Nonnested Comparisons

Row	Model 1 vs. Model 2	MSE_1/MSE_2	*MDM* test Test Statistic	*MDM* test p value
Panel A: Cointegrating Vector Reestimated				
1	$\hat{epi}_t$ vs. $r_t - r_{f,t}$	0.963	3.099**	0.002
2	$\hat{epi}_t$ vs. $d_t - p_t$ ♦	0.976	1.972	0.051
3	$\hat{epi}_t$ vs. $e_t - p_t$	0.970	2.740**	0.007
4	$\hat{epi}_t$ vs. $d_t - e_t$	0.948	2.405*	0.018
5	$\hat{epi}_t$ vs. $RREL_t$	0.963	3.003**	0.003
6	$\hat{epi}_t$ vs. $\hat{cay}_t$ ♦♦	0.991	1.561	0.121
7	$\hat{epi}_t$ vs. $\hat{cay}_t + \sigma_t$	0.967	2.556*	0.012
8	$\hat{epi}_t$ vs. $\hat{epb}_t$	0.949	2.699**	0.008
Panel B: Fixed Cointegrating Vector				
9	$\hat{epi}_t$ vs. $r_t - r_{f,t}$	0.960	3.435**	0.000
10	$\hat{epi}_t$ vs. $d_t - p_t$	0.973	2.660**	0.009
11	$\hat{epi}_t$ vs. $e_t - p_t$	0.967	2.374*	0.019
12	$\hat{epi}_t$ vs. $d_t - e_t$	0.946	2.969**	0.003
13	$\hat{epi}_t$ vs. $RREL_t$	0.960	3.513**	0.000
14	$\hat{epi}_t$ vs. $\hat{cay}_t$	0.996	2.982**	0.003
15	$\hat{epi}_t$ vs. $\hat{cay}_t + \sigma_t$	0.976	3.696**	0.000
16	$\hat{epi}_t$ vs. $\hat{epb}_t$	0.990	2.037*	0.044

Note: The *MDM* test, is a modified Diebold and Mariano (1995) test statistic to test for forecast encompassing between two non-nested models and to account for finite-sample biases. Model 1 always uses just lagged $\hat{epi}_t$ as a predictive variable; Model 2 uses one of several alternate variables. All of the models include a constant. The null hypothesis is that the model 2 encompasses model 1. We estimate the cointegration parameters recursively in panel A and using the full sample in panel B. The column labeled "MSE_1/MSE_2" reports the ratio of the root-mean-squared forecasting error of Model 1 to Model 2. A number less than one indicates that the model 1 has lower forecasting error than the model 2. The initial estimation period begins with the fourth quarter of 1953 and ends with the first quarter of 1968. The model is recursively reestimated until the second quarter of 2003. A * (**) denotes significance at the five (one) percent level. ♦ The inverse encompassing test that under the null model 1 encompasses model 2 is not rejected (p-value = 0.675). ♦♦ The inverse encompassing test that under the null model 1 encompasses model 2 is not rejected (p-value = 0.353).

Table 9. One-Quarter-Ahead Forecasts of Real Returns: Nonnested Comparisons

Row	Model 1 vs. Model 2	MSE_1/MSE_2	*MDM* test	
			Test Statistic	p value
		Panel A: Cointegrating Vector Reestimated		
1	$\hat{epi}_t$ vs. $r_t - r_{f,t}$	0.963	3.008**	0.003
2	$\hat{epi}_t$ vs. $d_t - p_t$ ♦	0.977	1.902	0.059
3	$\hat{epi}_t$ vs. $e_t - p_t$	0.972	2.803**	0.006
4	$\hat{epi}_t$ vs. $d_t - e_t$	0.950	2.433*	0.016
5	$\hat{epi}_t$ vs. $RREL_t$	0.968	2.880**	0.005
6	$\hat{epi}_t$ vs. $\hat{cay}_t$ ♦♦	0.992	1.512	0.133
7	$\hat{epi}_t$ vs. $\hat{cay}_t + \sigma_t$	0.967	2.593*	0.011
8	$\hat{epi}_t$ vs. $\hat{epb}_t$	0.950	2.698**	0.008
		Panel B: Fixed Cointegrating Vector		
9	$\hat{epi}_t$ vs. $r_t - r_{f,t}$	0.958	3.572**	0.000
10	$\hat{epi}_t$ vs. $d_t - p_t$	0.970	2.823**	0.005
11	$\hat{epi}_t$ vs. $e_t - p_t$	0.965	2.363*	0.019
12	$\hat{epi}_t$ vs. $d_t - e_t$	0.943	3.063**	0.003
13	$\hat{epi}_t$ vs. $RREL_t$	0.961	3.499**	0.000
14	$\hat{epi}_t$ vs. $\hat{cay}_t$	0.994	3.118*	0.002
15	$\hat{epi}_t$ vs. $\hat{cay}_t + \sigma_t$	0.974	3.798**	0.000
16	$\hat{epi}_t$ vs. $\hat{epb}_t$	0.980	2.356*	0.020

Note: See Table 8. ♦ The inverse encompassing test that under the null model 1 encompasses model 2 is not rejected (p-value = 0.671). ♦♦ The inverse encompassing test that under the null model 1 encompasses model 2 is not rejected (p-value = 0.376)

Table 10. Long-Horizon Regressions for Stock Prices Growth , Dividend Growth and Earning Growth

#	Regressors	Forecast Horizon *k*									
		1	2	3	4	8	12	16	20	24	48
		Panel A : Real Stock Prices Growth									
1	$e\hat{p}i_t$	**0.100**	**0.150**	**0.194**	**0.235**	**0.357**	**0.462**	**0.473**	**0.473**	0.461	**1.084**
		(3.042)	(3.274)	(3.464)	(3.584)	(4.992)	(4.005)	(3.462)	(2.516)	(1.904)	(4.067)
		[0.08]	[0.12]	[0.14]	[0.16]	[0.32]	[0.21]	[0.16]	[0.11]	[0.09]	[0.21]
2	$d_t - p_t$	0.039	0.062	0.088	0.112	0.193	0.248	0.238	0.309	**0.420**	**1.644**
		(1.249)	(1.372)	(1.525)	(1.622)	(1.769)	(1.885)	(1.605)	(1.834)	(2.043)	(5.711)
		[0.02]	[0.03]	[0.04]	[0.05]	[0.08]	[0.08]	[0.05]	[0.05]	[0.06]	[0.34]
3	$e_t - p_t$	0.029	0.047	0.068	0.088	0.136	0.166	0.131	0.129	0.156	**1.106**
		(0.988)	(1.127)	(1.322)	(1.446)	(1.393)	(1.331)	(0.951)	(0.769)	(0.772)	(4.527)
		[0.01]	[0.01]	[0.02]	[0.03]	[0.03]	[0.03]	[0.01]	[0.01]	[0.01]	[0.29]
		Panel B : Real Dividend Growth									
4	$e\hat{p}i_t$	**0.025**	**0.038**	**0.052**	**0.067**	**0.118**	**0.153**	**0.166**	**0.170**	**0.188**	**0.473**
		(3.130)	(3.213)	(3.440)	(3.707)	(4.310)	(4.480)	(4.174)	(3.580)	(3.511)	(8.168)
		[0.10]	[0.13]	[0.16]	[0.18]	[0.21]	[0.21]	[0.17]	[0.14]	[0.13]	[0.48]
5	$d_t - p_t$	0.001	0.004	0.007	0.011	0.040	**0.067**	**0.077**	0.071	0.090	**0.494**
		(0.209)	(0.364)	(0.477)	(0.662)	(1.495)	(2.112)	(2.022)	(1.608)	(1.722)	(5.420)
		[0.00]	[0.00]	[0.00]	[0.01]	[0.03]	[0.05]	[0.04]	[0.02]	[0.03]	[0.36]
6	$e_t - p_t$	0.001	0.001	0.003	0.005	0.019	0.030	0.022	0.000	0.000	**0.297**
		(0.164)	(0.195)	(0.198)	(0.279)	(0.620)	(0.744)	(0.477)	(0.007)	(0.016)	(3.993)
		[0.00]	[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.00]	[0.24]
		Panel C : Real Earning Growth									
7	$e\hat{p}i_t$	-0.003	0.001	0.013	0.031	0.089	0.056	-0.066	-0.157	-0.205	**0.438**
		(-0.073)	(0.015)	(0.151)	(0.297)	(0.622)	(0.371)	(-0.469)	(-1.092)	(-1.378)	(3.321)
		[0.00]	[0.00]	[0.00]	[0.00]	[0.01]	[0.00]	[0.00]	[0.02]	[0.04]	[0.17]

Note: The table reports estimates from OLS long-horizon regressions of real stock prices growth (Panel A), real dividend growth (panel B) and real earning growth (Panel C) on lagged variables. For each regression, the t-statistics, listed in parentheses, rely on a Newey-West correction. Adjusted R^2 statistics appear in square brackets. Significant coefficients at the five percent level are highlighted in bold. The sample period is fourth quarter of 1952 to third quarter 1998. Significant coefficients at the 5% level are highlighted in bold face. The sample period spans from fourth quarter of 1951 to the second quarter of 2003

Table 11. Long-horizon Regressions of Excess Returns

#	Regressors	Forecast Horizon k: 1	2	3	4	8	12	16	20	24	48
1	$c\hat{a}y_t$	**3.452**	**5.003**	**6.294**	**7.688**	**11.465**	**13.458**	**13.235**	**11.972**	**10.344**	3.154
		(4.542)	(4.787)	(5.287)	(5.616)	(4.992)	(5.128)	(4.568)	(4.053)	(2.813)	(0.615)
		[0.138]	[0.188]	[0.218]	[0.256]	[0.323]	[0.327]	[0.245]	[0.153]	[0.096]	[0.00]
2	$e\hat{p}i_t$	**0.139**	**0.193**	**0.246**	**0.295**	**0.495**	**0.648**	**0.674**	**0.635**	**0.583**	**0.744**
		(4.535)	(4.380)	(4.356)	(4.395)	(4.746)	(5.001)	(4.808)	(3.771)	(3.044)	(3.747)
		[0.155]	[0.195]	[0.229]	[0.256]	[0.380]	[0.425]	[0.379]	[0.262]	[0.191]	[0.185]
3	$e\hat{p}b_t$	**0.123**	**0.176**	**0.220**	**0.260**	**0.424**	**0.561**	**0.609**	**0.628**	**0.635**	**0.911**
		(4.013)	(4.063)	(3.999)	(4.002)	(4.441)	(4.965)	(4.999)	(4.551)	(4.005)	(5.468)
		[0.135]	[0.179]	[0.203]	[0.224]	[0.323]	[0.384]	[0.372]	[0.304]	[0.258]	[0.316]
5	$d_t - p_t$	**0.096**	**0.142**	**0.188**	**0.232**	**0.408**	**0.549**	**0.670**	**0.830**	**0.969**	**1.583**
		(3.333)	(3.485)	(3.646)	(3.787)	(4.740)	(5.783)	(7.084)	(8.469)	(8.668)	(9.030)
		[0.107]	[0.151]	[0.192]	[0.227]	[0.378]	[0.448]	[0.492]	[0.518]	[0.526]	[0.584]
6	$e_t - p_t$	**0.086**	**0.126**	**0.165**	**0.200**	**0.355**	**0.475**	**0.524**	**0.574**	**0.620**	**1.167**
		(3.097)	(3.235)	(3.344)	(3.417)	(3.870)	(3.975)	(4.050)	(3.964)	(3.970)	(8.262)
		[0.084]	[0.118]	[0.147]	[0.170]	[0.278]	[0.326]	[0.334]	[0.311]	[0.304]	[0.601]
7♦	$c\hat{a}y_t$	**2.604**	0.115	**4.998**	**6.130**	**9.176**	**10.043**	**9.448**	**9.571**	**10.274**	-1.615
		(3.553)	(2.189)	(4.659)	(4.943)	(5.304)	(5.769)	(5.124)	(4.854)	(3.778)	(-0.583)
	$e\hat{p}i_t$	**0.127**	**3.927**	**0.211**	**0.240**	**0.346**	**0.443**	**0.513**	**0.545**	**0.510**	**0.560**
		(4.189)	(4.138)	(3.855)	(3.745)	(4.170)	(5.068)	(5.517)	(3.861)	(3.079)	(2.278)
	$d_t - e_t$	-0.028	-0.036	-0.017	0.001	0.050	0.062	0.242	**0.499**	0.514	**-1.337**
		(-0.531)	(-0.508)	(-0.198)	(0.005)	(0.401)	(0.470)	(1.371)	(2.077)	(1.697)	(-3.454)
	$RREL_t$	**-1.785**	**-2.651**	-2.794	-2.742	0.450	3.155	5.301	**7.101**	**6.207**	4.953
		(-2.010)	(-2.168)	(-1.748)	(-1.581)	(0.295)	(1.609)	(2.138)	(2.717)	(2.101)	(1.131)
	DEF_t	0.605	0.393	0.953	1.818	3.591	**9.920**	**20.162**	**30.972**	**35.475**	**36.410**
		(0.286)	(0.138)	(0.268)	(0.450)	(0.764)	(2.491)	(3.557)	(4.350)	(4.565)	(3.623)
	TRM_t	-0.433	-0.856	-1.393	-1.686	-1.658	0.539	2.906	2.295	-0.587	8.095
		(-0.507)	(-0.776)	(-1.034)	(-1.033)	(-0.766)	(0.245)	(1.033)	(0.682)	(-0.161)	(1.796)
		[0.248]	[0.325]	[0.365]	[0.402]	[0.526]	[0.593]	[0.583]	[0.499]	[0.392]	[0.601]
8♦	$c\hat{a}y_t$	**2.601**	**3.886**	**4.968**	**6.128**	**9.170**	**9.828**	**8.867**	**8.905**	**10.220**	-2.871
		(3.639)	(4.142)	(4.570)	(4.774)	(4.734)	(4.940)	(4.359)	(4.162)	(3.932)	(-1.201)
	$e\hat{p}b_t$	**0.106**	**0.147**	**0.178**	**0.201**	**0.278**	**0.372**	**0.486**	**0.605**	**0.668**	**0.816**
		(2.999)	(3.038)	(2.984)	(2.919)	(3.321)	(4.365)	(5.620)	(5.982)	(5.985)	(3.661)
	$d_t - e_t$	-0.016	-0.019	0.002	0.022	0.089	0.115	0.321	**0.628**	**0.736**	-0.636
		(-0.276)	(-0.250)	(0.020)	(0.202)	(0.634)	(0.795)	(1.856)	(3.193)	(3.401)	(-1.479)
	$RREL_t$	-1.239	-1.906	-1.879	-1.682	2.086	**5.131**	**7.906**	**10.333**	**10.526**	**13.033**
		(-1.322)	(-1.457)	(-1.094)	(-0.896)	(1.216)	(2.319)	(3.230)	(5.032)	(4.391)	(3.137)
	DEF_t	0.424	0.139	0.665	1.496	3.437	9.591	**19.874**	**31.244**	**37.746**	**48.775**
		(0.185)	(0.045)	(0.169)	(0.326)	(0.577)	(1.581)	(2.643)	(4.233)	(5.116)	(5.725)
	TRM_t	-0.115	-0.408	-0.826	-1.006	-0.490	2.140	4.981	4.504	1.762	**10.960**
		(-0.131)	(-0.352)	(-0.582)	(-0.568)	(-0.199)	(1.023)	(1.929)	(1.493)	(0.590)	(3.005)
		[0.218]	[0.295]	[0.328]	[0.366]	[0.478]	[0.555]	[0.585]	[0.566]	[0.499]	[0.666]
9♦	$c\hat{a}y_t$	**2.469**	**3.594**	**4.502**	**5.517**	**7.785**	**8.223**	**7.053**	**6.874**	**8.152**	**-7.272**
		(3.151)	(3.514)	(3.786)	(3.900)	(3.850)	(3.798)	(3.017)	(2.974)	(3.373)	(-2.713)
	$d_t - p_t$	**0.094**	**0.140**	**0.180**	**0.209**	**0.347**	**0.445**	**0.575**	**0.759**	**0.928**	**1.246**
		(2.515)	(2.746)	(2.851)	(2.851)	(4.016)	(4.481)	(5.960)	(6.862)	(9.284)	(4.908)
	$d_t - e_t$	-0.080	-0.114	-0.118	-0.117	-0.152	-0.191	-0.052	0.179	0.256	**-0.905**
		(-1.371)	(-1.460)	(-1.257)	(-1.095)	(-1.127)	(-1.281)	(-0.301)	(1.006)	(1.437)	(-3.210)
	$RREL_t$	**-1.958**	**-2.958**	-3.218	-3.248	-0.621	1.853	3.790	**5.151**	**5.153**	**7.743**
		(-2.011)	(-2.206)	(-1.869)	(-1.759)	(-0.349)	(0.896)	(1.583)	(2.299)	(2.345)	(2.069)
	DEF_t	-3.375	-5.541	-6.705	-7.094	-11.400	-9.253	-4.146	0.244	1.100	8.609
		(-1.213)	(-1.563)	(-1.529)	(-1.386)	(-1.680)	(-1.418)	(-0.567)	(0.032)	(0.152)	(0.924)
	TRM_t	0.281	0.232	0.007	-0.045	0.985	3.979	**7.347**	**7.420**	**5.602**	**15.271**
		(0.311)	(0.195)	(0.005)	(-0.026)	(0.434)	(1.958)	(2.726)	(2.603)	(1.966)	(4.223)
		[0.198]	[0.283]	[0.326]	[0.368]	[0.521]	[0.586]	[0.615]	[0.619]	[0.601]	[0.718]

Note: The table reports estimates from OLS long-horizon regressions of excess returns on lagged variables. For each regression, the t-statistics, listed in parentheses, rely on a Newey-West correction. Adjusted R^2 statistics appear in square brackets. Significant coefficients at the five percent level are highlighted in bold. The sample period is fourth quarter of 1952 to third quarter 1998. Significant coefficients at the 5% level are highlighted in bold face. The sample period spans from fourth quarter of 1951 to the second quarter of 2003, except for regression 7, 8 and 9 (indicated by ♦), which begins in the second quarter of 1953, the largest common sample for which all the data are available.

Table 12. Long-horizon Regressions of Real Stock Returns

#	Regressors	Forecast Horizon k									
		1	2	3	4	8	12	16	20	24	48
1	$c\hat{a}y_t$	**0.094**	**5.193**	**6.543**	**8.004**	**12.094**	**14.446**	**14.827**	**14.429**	**13.865**	7.270
		(4.555)	(4.822)	(5.320)	(5.684)	(5.329)	(5.560)	(5.041)	(4.569)	(3.431)	(1.158)
		[0.144]	[0.195]	[0.223]	[0.259]	[0.322]	[0.328]	[0.258]	[0.182]	[0.137]	[0.012]
2	$e\hat{p}i_t$	**0.143**	**0.200**	**0.254**	**0.303**	**0.505**	**0.659**	**0.695**	**0.671**	**0.637**	**0.829**
		(4.554)	(4.456)	(4.451)	(4.483)	(4.711)	(4.818)	(4.616)	(3.710)	(3.051)	(3.594)
		[0.159]	[0.199]	[0.230]	[0.253]	[0.353]	[0.383]	[0.337]	[0.238]	[0.179]	[0.158]
3	$e\hat{p}b_t$	**0.117**	**0.167**	**0.208**	**0.246**	**0.400**	**0.527**	**0.575**	**0.599**	**0.626**	**0.013**
		(3.615)	(3.662)	(3.605)	(3.600)	(3.890)	(4.263)	(4.326)	(4.046)	(3.699)	(5.119)
		[0.116]	[0.153]	[0.171]	[0.186]	[0.256]	[0.294]	[0.276]	[0.223]	[0.195]	[0.268]
5	$d_t - p_t$	**0.096**	**0.144**	**0.190**	**0.235**	**0.417**	**0.564**	**0.699**	**0.880**	**1.058**	**1.911**
		(3.251)	(3.432)	(3.598)	(3.750)	(4.743)	(5.764)	(6.953)	(8.232)	(8.526)	(9.525)
		[0.103]	[0.147]	[0.185]	[0.217]	[0.353]	[0.413]	[0.447]	[0.473]	[0.490]	[0.587]
6	$e_t - p_t$	**0.086**	**0.128**	**0.168**	**0.205**	**0.367**	**0.496**	**0.560**	**0.362**	**0.711**	**1.449**
		(3.027)	(3.203)	(3.346)	(3.450)	(3.965)	(4.088)	(4.188)	(4.067)	(4.056)	(9.528)
		[0.082]	[0.117]	[0.145]	[0.166]	[0.266]	[0.309]	[0.320]	[0.306]	[0.313]	[0.640]
7♦	$c\hat{a}y_t$	**0.067**	**4.071**	**5.203**	**6.415**	**9.868**	**11.153**	**11.126**	**12.091**	**13.905**	1.912
		(3.574)	(4.140)	(4.559)	(4.779)	(5.243)	(5.614)	(5.193)	(5.315)	(4.807)	(0.565)
	$e\hat{p}i_t$	**2.680**	**0.177**	**0.218**	**0.247**	**0.348**	**0.444**	**0.528**	**0.583**	**0.577**	**0.637**
		(4.249)	(4.008)	(3.921)	(3.783)	(4.006)	(4.735)	(5.400)	(4.115)	(3.442)	(2.415)
	$d_t - e_t$	-0.031	-0.040	-0.024	-0.008	0.047	0.062	0.234	**0.490**	**0.509**	**-1.668**
		(-0.552)	(-0.527)	(-0.257)	(-0.071)	(0.336)	(0.402)	(1.237)	(2.061)	(1.705)	(-3.850)
	$RREL_t$	-1.839	-2.723	-2.859	-2.811	0.690	3.709	**6.283**	**8.595**	**8.138**	7.571
		(-2.124)	(-2.204)	(-1.743)	(-1.555)	(0.388)	(1.686)	(2.376)	(3.181)	(2.677)	(1.569)
	DEF_t	1.303	1.534	2.490	3.795	7.583	**15.245**	**26.266**	**38.193**	**44.450**	**50.101**
		(0.632)	(0.546)	(0.700)	(0.903)	(1.325)	(2.729)	(3.567)	(4.566)	(5.028)	(4.482)
	TRM_t	-0.421	-0.907	-1.481	-1.821	-2.085	-0.046	2.517	2.150	-0.475	9.837
		(-0.492)	(-0.807)	(-1.066)	(-1.051)	(-0.844)	(-0.018)	(0.781)	(0.556)	(-0.115)	(1.873)
		[0.263]	[0.340]	[0.377]	[0.411]	[0.513]	[0.576]	[0.576]	[0.526]	[0.455]	[0.648]
8♦	$c\hat{a}y_t$	**2.798**	**4.208**	**5.397**	**6.676**	**10.234**	**11.409**	**10.951**	**11.632**	**13.897**	0.540
		(3.786)	(4.264)	(4.600)	(4.748)	(4.756)	(4.908)	(4.505)	(4.544)	(4.864)	(0.176)
	$e\hat{p}b_t$	**0.096**	**0.132**	**0.159**	**0.178**	**0.235**	**0.313**	**0.431**	**0.567**	0.669	**0.913**
		(2.519)	(2.516)	(2.444)	(2.358)	(2.474)	(3.138)	(4.244)	(4.907)	(5.336)	(3.781)
	$d_t - e_t$	-0.019	-0.023	-0.005	0.013	0.087	0.115	0.301	**0.598**	0.712	-0.889
		(-0.312)	(-0.284)	(-0.050)	(0.114)	(0.553)	(0.674)	(1.545)	(2.813)	(3.220)	(-1.906)
	$RREL_t$	-1.298	-1.987	-1.952	-1.770	2.293	**5.483**	**8.660**	**11.667**	**12.413**	**16.610**
		(-1.362)	(-1.443)	(-1.068)	(-0.867)	(1.108)	(2.119)	(3.079)	(4.784)	(4.685)	(3.603)
	DEF_t	1.147	1.317	2.252	3.534	7.612	15.044	**25.944**	**38.181**	**46.303**	**63.741**
		(0.476)	(0.406)	(0.540)	(0.712)	(1.081)	(1.927)	(2.672)	(3.910)	(4.725)	(6.417)
	TRM_t	-0.156	-0536	-1.009	-1.251	-1.042	1.377	4.450	**4.407**	**2.032**	**13.119**
		(-0.168)	(-0.426)	(-0.645)	(-0.632)	(-0.364)	(0.513)	(1.391)	(1.195)	(0.570)	(3.139)
		[0.211]	[0.283]	[0.311]	[0.346]	[0.437]	[0.501]	[0.527]	[0.532]	[0.503]	[0.699]
9♦	$c\hat{a}y_t$	**2.640**	**3.874**	**4.880**	**6.010**	**8.830**	**9.768**	**9.050**	**9.513**	**11.701**	-4.491
		(3.266)	(3.619)	(3.817)	(3.893)	(3.909)	(3.886)	(3.311)	(3.524)	(4.556)	(-1.366)
	$d_t - p_t$	**0.089**	**0.132**	**0.170**	**0.196**	**0.315**	**0.403**	**0.545**	**0.753**	**0.977**	**1.413**
		(2.262)	(2.479)	(2.567)	(2.554)	(3.289)	(3.695)	(5.240)	(6.434)	(9.426)	(5.350)
	$d_t - e_t$	-0.079	-0.113	-0.118	-0.117	-0.132	-0.162	-0.046	0.165	0.226	**-1.179**
		(-1.249)	(-1.318)	(-1.152)	(-1.005)	(-0.836)	(-0.887)	(-0.225)	(0.791)	(1.122)	(-3.861)
	$RREL_t$	**-1.970**	**-2.969**	-3.204	-3.219	-0.151	2.595	4.889	**6.685**	**6.996**	**10.732**
		(-2.023)	(-2.154)	(-1.791)	(-1.656)	(-0.073)	(1.069)	(1.788)	(2.557)	(2.802)	(2.580)
	DEF_t	-2.447	-4.068	-4.722	-4.533	-5.946	-2.086	3.188	7.547	8.018	**18.543**
		(-0.863)	(-1.128)	(-1.061)	(-0.852)	(-0.756)	(-0.257)	(0.345)	(0.794)	(0.866)	(1.812)
	TRM_t	0.236	0.099	-0.183	-0.305	0.351	3.117	**6.779**	**7.345**	6.132	**17.988**
		(0.248)	(0.077)	(-0.116)	(-0.154)	(0.127)	(1.170)	(2.076)	(2.106)	(1.844)	(4.205)
		[0.199]	[0.281]	[0.319]	[0.358]	[0.480]	[0.538]	[0.569]	[0.594]	[0.607]	[0.746]

Note: The table reports estimates from OLS long-horizon regressions of real stock returns on lagged variables. For each regression, the t-statistics, listed in parentheses, rely on a Newey-West correction. Adjusted R^2 statistics appear in square brackets. Significant coefficients at the five percent level are highlighted in bold. The sample period is fourth quarter of 1952 to third quarter 1998. Significant coefficients at the 5% level are highlighted in bold face. The sample period spans from fourth quarter of 1951 to the second quarter of 2003, except for regression 7, 8 and 9 (indicated by ♦), which begins in the second quarter of 1953, the largest common sample for which all the data are available.

Table 13. Long Horizon Forecasts of Excess Returns: Nested Models

k	1	2	3	4	8	12	16	20	24	48
Panel A : Excess Returns										
Panel A: Reestimated $e\hat{p}i_t$ vs. C										
MSE_u/MSE_r	0.941	0.898	0.859	0.842	0.850	0.783	0.764	0.818	0.846	0.653
ENC-NEW	**8.992**	**14.497**	**17.997**	**20.160**	**16.080**	**24.555**	**31.709**	27.279	25.408	**30.469**
(p-value)	(0.000)	(0.004)	(0.004)	(0.008)	(0.048)	(0.040)	(0.036)	(0.053)	(0.068)	(0.045)
MSE-F	**9.032**	**15.886**	**22.742**	**25.976**	**23.692**	**36.120**	**38.977**	**27.231**	21.432	**50.043**
(p-value)	(0.000)	(0.001)	(0.000)	(0.002)	(0.014)	(0.012)	(0.018)	(0.035)	(0.058)	(0.028)
Panel A2: Fixed $e\hat{p}i_t$ vs. C										
MSE_u/MSE_r	0.926	0.879	0.824	0.812	0.800	0.754	0.803	0.921	1.030	1.193
ENC-NEW	**16.208**	**25.715**	**32.222**	**36.028**	**27.683**	**33.378**	**32.769**	21.657	11.852	2.871
(p-value)	(0.000)	(0.000)	(0.000)	(0.001)	(0.021)	(0.027)	(0.048)	(0.088)	(0.170)	(0.373)
MSE-F	**11.135**	**19.294**	**27.620**	31.929	**33.578**	**42.406**	**30.924**	10.417	-3.480	-15.195
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.007)	(0.011)	(0.032)	(0.105)	(0.307)	(0.664)
Panel B : Real Returns										
Panel B1: Reestimated $e\hat{p}i_t$ vs. C										
MSE_u/MSE_r	0.942	0.904	0.871	0.859	0.886	0.839	0.831	0.872	0.882	0.670
ENC-NEW	**8.498**	**13.388**	**16.054**	**17.298**	11.786	17.056	21.294	19.146	19.086	27.578
(p-value)	(0.001)	(0.004)	(0.007)	(0.012)	(0.078)	(0.069)	(0.066)	(0.091)	(0.099)	(0.054)
MSE-F	**8.704**	**14.960**	**20.625**	**22.686**	**17.206**	**24.855**	**25.555**	17.899	15.787	**46.209**
(p-value)	(0.000)	(0.001)	(0.002)	(0.004)	(0.027)	(0.024)	(0.034)	(0.062)	(0.081)	(0.033)
Panel B2: Fixed $e\hat{p}i_t$ vs. C										
MSE_u/MSE_r	0.920	0.870	0.827	0.808	0.817	0.789	0.824	0.908	0.993	1.099
ENC-NEW	**17.221**	**26.920**	**32.798**	**35.589**	**24.175**	**26.965**	26.811	19.425	11.454	3.302
(p-value)	(0.000)	(0.000)	(0.000)	(0.001)	(0.027)	(0.042)	(0.061)	(0.101)	(0.184)	(0.359)
MSE-F	**12.288**	**20.979**	**29.146**	**32.820**	**29.992**	**34.731**	**26.985**	12.361	0.828	-8.436
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.015)	(0.037)	(0.100)	(0.221)	(0.533)

Note: The *MSE-F* statistic is used to test the null hypothesis that the MSE for the unrestricted model forecasts is less than or equal to the MSE for the restricted model forecasts. The *ENC-NEW* statistic is used to test the null hypothesis that restricted model forecasts encompass the unrestricted model forecasts. The dependent variable in Panel A is the *k*-period log excess returns. In Panel B, the dependent variable is the *k*-period log real stock returns. We estimate the cointegration parameters recursively in panel A1 and B1 and using the full sample in panel A2 and B2. We consider a restricted (benchmark) model of constant returns. The rows labeled "MSE_u/MSE_r" report the ratio of the root-mean-squared forecasting error of the unrestricted model 1 to the restricted model. A number less than one indicates that the unrestricted model has lower forecasting error than the restricted model. The initial estimation period begins with the fourth quarter of 1953 and ends with the first quarter of 1968. The model is recursively reestimated until the second quarter of 2003. The p-values are calculated using a bootstrap based on Kilian (1999). The p-value provides a measure of the rate at which null hypotheses are rejected. Significant coefficients at the 5% level are highlighted in bold face.

Figure 1. Excess Returns and transitory deviations from the common trend in the earning-price ratio and inflation

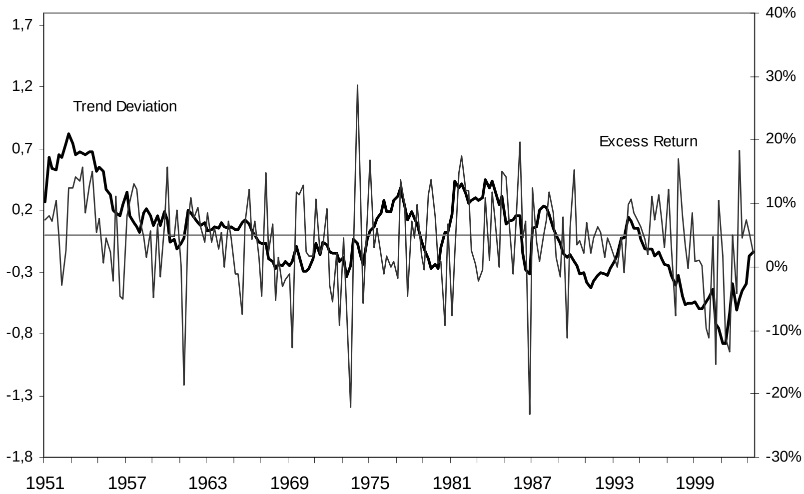


Figure 2. recursively estimated coefficient on inflation

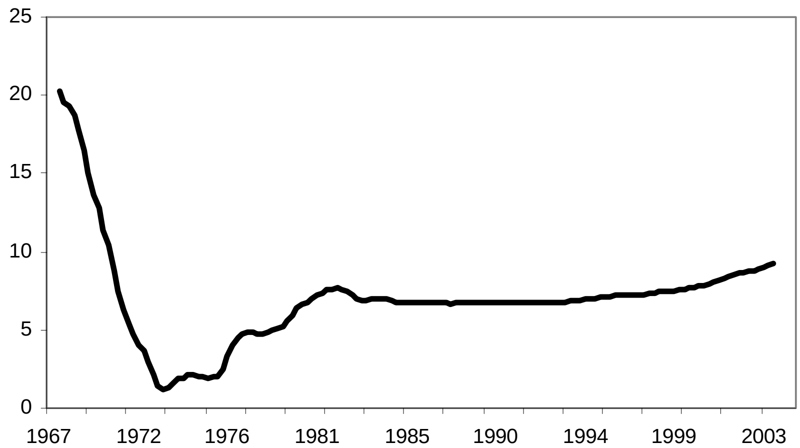
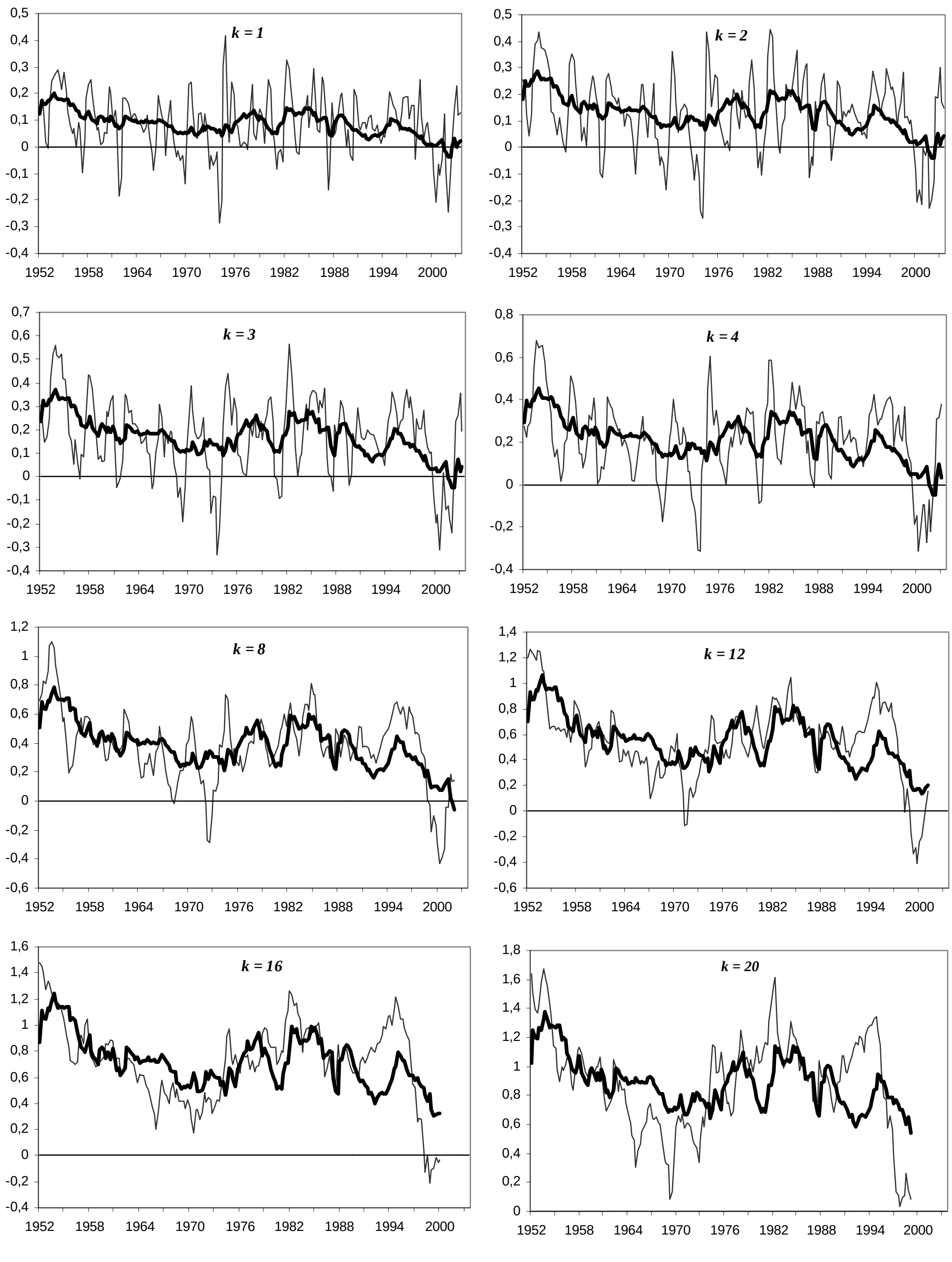


Figure 3. Predicted and realized excess returns at long-horizons



Note: The figure shows realized and predicted excess returns at different horizons by an univariate model with $e\hat{p}i_t$ as the sole predictor. The predictions are based upon the log earning-price ratio. The gray line represents the realized excess returns and the black line represents the predicted excess returns.

Appendix 1 Additional Tables

Table A1. Unit root and stationary tests

	variables in level			variables in differences		
	ADF	lags	KPSS	ADF	lags	KPSS
$e_t - p_t$	-2.03	1	3.37	**-8.10**	3	**0.05**
$d_t - p_t$	-1.09	0	9.97	**-13.38**	0	**0.09**
p_t	-1.56	1	6.33	**-13.03**	0	**0.16**
e_t	-2.16	7	1.95	**-6.48**	6	**0.04**
d_t	-2.73	8	1.74	**-5.47**	7	**0.30**
π_t	-1.86	8	0.53	**-8.48**	7	**0.05**
tb_t	-2.07	7	1.10	**-6.22**	6	**0.15**
$d_t - e_t$	**-3.49**	5	**0.46**			
rf_t	**-4.11**	7	**0.34**			

Note: The ADF test statistics highlighted in bold face type are above the critical value at the five percent significance level. The KPSS statistics highlighted in bold face type are below the critical value at the five percent significance level. ADF and KPSS critical values are from Hamilton (1994). The maximum lags considered is 8. AIC is used to selct the lag length. The sample period is firth quarter of 1948 to firth quarter of 2004.

Table A2. Forecasting Quarterly Excess Returns with different specifications for the normalized stock prices

#	Constant (*t*-stat)	$e1_t - p_t$ (*t*-stat)	$e5_t - p_t$ (*t*-stat)	$e10_t - p_t$ (*t*-stat)	$d1_t - p_t$ (*t*-stat)	$d5_t - p_t$ (*t*-stat)	$d10_t - p_t$ (*t*-stat)	$e\hat{p}i_t$ (*t*-stat)	$d\hat{p}i_t$ (*t*-stat	$\bar{R}^2$
Panel A: Excess Returns										
1	**0.211** (4.742)				**0.049** (3.800)					0.061
2	**0.205** (4.560)					**0.047** (3.627)				0.056
3	**0.192** (4.291)						**0.043** (3.351)			0.047
4	**0.043** (8.669)							**0.072** (4.418)		0.094
5	**0.043** (8.389)								**0.061** (3.922)	0.085
6	**0.162** (4.499)	**0.043** (3.336)								0.047
7	**0.156** (4.327)		**0.041** (3.6169							0.042
8	**0.152** (4.321)			**0.039** (3.132)						0.041
Panel B: Real Returns										
9	**0.213** (3.878)				**0.049** (3.011)					0.059
10	**0.206** (3.623)					**0.046** (2.801)				0.053
11	**0.192** (3.450)						**0.042** (2.631)			0.044
12	**0.046** (9.022)							**0.074** (4.381)		0.096
13	**0.046** (8.703)								**0.062** (3.830)	0.085
14	**0.165** (3.825)	**0.043** (2.802)								0.046
15	**0.159** (3.596)		**0.041** (2.566)							0.041
16	**0.156** (3.659)			**0.039** (2.594)						0.041

Note: The table reports estimates from OLS regressions of stock returns on lagged variables named at the head of a column. The variables labeled "$en_t - p_t$" are the log ratio of *n*-year average earnings to stock prices. The variables labeled "$dn_t - p_t$" are the log ratio of *n*-year average dividends to stock prices. $d\hat{p}i_t$ is the log dividend-price inflation ratio. Regressions use data from the fourth quarter of 1951 to the second quarter of 2003. Newey–West corrected t-statistics appear in parentheses below the coefficient estimate. Significant coefficients at the 5% level are highlighted in bold face. The sample period is fourth quarter of 1951 to second quarter of 2003.

Table A3. Forecasting Quarterly Excess Returns with different specifications of the log earning-price ratio

#	Constant (*t*-stat)	$e\hat{p}i_t$ (*t*-stat)	$e\hat{p}i_t^{(12l)}$ (*t*-stat)	$e\hat{p}i_t^{(4l)}$ (*t*-stat)	$e\hat{p}i_t^{(Joh)}$ (*t*-stat)	$e\hat{p}i_t^{(-1)}$ (*t*-stat)	$\overline{R}^2$
			Panel A: Excess Returns				
1	**0.044** (8.807)					**0.072** (4.423)	0.094
2	**0.017** (1.990)				**0.070** (4.366)		0.092
3	**0.043** (8.638)			**0.071** (4.395)			0.093
4	**0.043** (8.632)		**0.073** (4.408)				0.094
5	**0.043** (8.669)	**0.072** (4.418)					0.094
			Panel B: Real Returns				
6	**0.047** (9.146)					**0.074** (4.380)	0.096
7	**0.019** (2.269)				**0.072** (4.352)		0.095
8	**0.046** (9.000)			**0.073** (4.371)			0.096
9	**0.046** (8.971)		**0.074** (4.353)				0.096
10	**0.046** (9.022)	**0.074** (4.382)					0.096

Note: The table reports estimates from OLS regressions of stock returns on lagged variables named at the head of a column. Regressions use data from the fourth quarter of 1951 to the second quarter of 2003. The regressors are as follows: $e\hat{p}i_t^{(12l)}$ and $e\hat{p}i_t^{(4l)}$ are the log earning-price ratio estimated respectively with 12 and 4 lead/lag lengths in estimating the DOLS specification; $e\hat{p}i_t^{(Joh)}$ is the log earning-price ratio with the cointegrating parameters obtained in section 3 based on Johansen's (1988) full information maximum likelihood approach; $e\hat{p}i_t^{(-1)}$ is the log earning-price lag inflation ratio (from the cointegration relationship among the earning-price ratio and one lag of inflation). Newey–West corrected t-statistics appear in parentheses below the coefficient estimate. Significant coefficients at the 5% level are highlighted in bold face.

Appendix 2 Out of sample tests statistics for nested models

The sample is divided into in-sample and out-of-sample portions. The in-sample portion spans observations 1 to R. Letting $P - k + 1$ denote the number of k -step ($1 \leq k$) ahead forecasts, the out-of-sample observations span R + k through $R + P$. The total number of observations in the sample is $R + P = T$.

Calculation/definition of test statistics for equal *MSE*

The McCracken (2004) *MSE-F* statistic is a variant of the Diebold and Mariano (1995) and West (1996) statistic designed to test for equal predictive ability. The *MSE-F* statistic is used to test the null hypothesis that the unrestricted model forecast MSE is equal to the restricted model forecast MSE against the one-sided (upper-tail) alternative hypothesis that the unrestricted model forecast MSE is less than the restricted model forecast MSE.

Let $\hat{d}_{t+k} = (\hat{u}_{1,t+k})^2 - (\hat{u}_{2,t+k})^2$ and $\overline{d} = (P - k + 1)^{-1} \sum_{t=R}^{T-k} \hat{d}_{t+k} = MSE_1 - MSE_2$, where $MSE_i = \sum_{t=R}^{T-k} (\hat{u}_{i,t+k})^2$, $i = 1, 2$, the McCracken (2004) *MSE-F* statistic is given by:

$$MSE\text{-}F = (P - k + 1) \cdot \overline{d} \,/\, MSE_2 \tag{1}$$

Under the null that the mean square error associated with model 1 is the same as that for model 2, the expected difference between $u_{1,t+k}^2$ and $u_{2,t+k}^2$ is zero. Under the alternative the mean square error associated with model 2 (unrestricted model) will be smaller than that for model 1 (restricted model).

Calculation/definition of test statistics for forecast encompassing

The Clark and McCracken (2001) *ENC-NEW* statistic is a variant of the Harvey, Leybourne, and Newbold (1998) statistic to test for forecast encompassing between two non-nested models.

Let $\overline{c} = (P-k+1)^{-1}\sum_{t=R}^{T-k}\hat{c}_{t+k}$ and $\hat{c}_{t+k} = \hat{u}_{1,t+k}(\hat{u}_{1,t+k} - \hat{u}_{2,t+k})$. The Clark and McCracken (2001) *ENC-NEW* statistic is given by:

$$ENC\text{-}NEW = (P-k+1)\cdot \overline{c} \,/\, MSE_2 \tag{2}$$

Under the null that the forecast from model 1 (restricted) encompasses that of model 2 (unrestricted), the covariance between $u_{1,t+k}$ and $u_{1,t+k} - u_{2,t+k}$ will be less than or equal to zero. Under the alternative that model 2 contains added information, the covariance should be positive.

The *MSE-F* and *ENC-NEW* statistics have key power advantages over the original Diebold and Mariano (1995), West (1996) and Harvey, Leybourne, and Newbold (1998) statistics according to extensive Monte Carlo simulations in Clark and McCracken (2001, 2004).

The limiting distributions of the *MSE-F* and *ENC-NEW* statistics are non-standard and pivotal for k = 1 (Clark and McCracken, 2001) when comparing forecasts from nested models. Since the remaining tests have non-standard and non-pivotal limiting distributions for k > 1 that are usually dependent upon unknown nuisance parameters, we follow Clark and McCracken (2004) in using a bootstrap similar to that in Kilian (1999) to estimate asymptotically valid critical values and construct asymptotically valid p-values.

Appendix 3 Bootstrap Procedure

The p-values associated with the *MSE-F* and *ENC-NEW* statistics are estimated using a bootstrap similar to that discussed in Kilian (1999) and used by Clark and McCracken (2004). Following Rapach and Wohar (2004b), we postulate that the data are generated by the following system under the null hypothesis of no predictability:

$$y_t = \alpha_0 + \varepsilon_{1,t} \tag{1}$$

$$x_t = \beta_0 + \sum_{i=1}^{p} \beta_i \cdot x_{t-i} + \varepsilon_{2,t} \tag{2}$$

where the number of lags, *p*, is determined using AIC.

We compute the OLS residuals from estimated equations (1) and (2) and sample them with replacement to obtain a set of bootstrap residuals, $\varepsilon_{1,t}^{*}$ and $\varepsilon_{2,t}^{*}$. We create the bootstrap series y_t^{*} and x_t^{*} recursively using these bootstrap residuals and the estimated coefficients.

For the bootstrap series, we calculate the two tests statistics outlined in appendix 2. For each test statistic, critical values are simply computed as percentiles of the bootstrapped test statistics. Following Kilian (1999), the number of bootstrap draws is 2000.