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Stock Prices, Inflation and Stock Returns Predictability

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1. Introduction

In this article, we provide new evidence of the out-of-sample predictability of stock returns. We assume a time-varying risk premium which can be expressed as a linear function of the rate of 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 out-of-sample forecasting abilities for real stock 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;

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Feldstein, 1980; and more recently, Sharpe, 2002; Campbell and Vuolteenaho, 2004).

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. Also, Campbell and 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.

Despite the econometric difficulties relating to the overlapping observations, highly persistent predictor variables and 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 predictive regressions have often performed poorly out-of-sample[1]. On the other hand, Valkanov (2003), Campbell and Yogo (2004), Torous *et al*. (2004) reexamine the evidence for predictability using tests that have the correct size even if the predictor variable is highly persistent 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

1. 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.

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 previous studies explicitly exclude the possibility that valuation ratios are not mean reverting and therefore non-stationary. However, Goyal and Welch (2003), among others, cannot reject that dividend yield contain an unit-root over the longest sample period available at quarterly frequency (since 1926)[2]. 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, this implies a permanent drop in the dividend-price ratio and then the non-stationarity of the valuation ratio. This is the way that we followed.

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

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

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)[3] and was confirmed more recently (Graham, 1996; Siklos and Kwok, 1999; Barnes *et al*., 1999).

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 which is the starting point of our analysis.

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 include: (i) a correlation between expected inflation and expected real economic growth (the "proxy hypothesis" suggested by Fama 1981)[4]; (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 US

3. 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).

4. 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 monetizes a portion of fiscal deficits, the money supply increases, which in turn increases inflation.

inflation non-neutralities tax code which distorts accounting profits (Feldstein, 1980).

In the present value model, a low dividend-price ratio or earning-price ratio imply either that cash-flows are expected to grow rapidly, stock returns are expected to be low in the future, or some combination of the two. Thus, the difficulty with the first explanation concerning the inflation-valuation ratio relationship is that if such a relation exists, then it will concern the expected growth over business cycle horizons (*i.e.* ranging from one quarter to few years) instead of long-term real cash-flow growth. Moreover, a large literature has documented the poor predictability of real dividend growth and real output growth by the valuation ratios (*e.g.* Campbell, 2003). Also the fourth explanation is less convincing since the empirical evidence of the negative stock-return relation is also provided at international level and since 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.

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)[5] and they fail to recognize the capital gain that accrues to the equity holders of firms with fixed dollar liabilities in the presence of inflation. Ritter and Warr (2002) 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. Also, Campbell and Vuolteenaho (2004) recently provided empirical evidence of money illusion. These authors 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

5. The use of the "Fed model" by Wall Street which relates the yield on stocks to the yield on nominal Treasury bonds illustrates the money illusion of financial analysts (see Asness, 2003).

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[6], 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 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. Sharpe (2002) examined the effect of inflation forecasts on required (long-run) real stock returns over the period 1983-2001 and found that this effect is substantial. In his model, the log earnings-price ratio is expressed as a linear function of expected 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. Sharpe (2002) evaluates that 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[7]. 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. In the next sections, we will attempt to discriminate between these two alternative hypotheses : the money illusion hypothesis and the subjective inflation risk premium hypothesis.

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6. 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.

7. 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.

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:

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

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:

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

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[8]. 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

8. 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.

$\pi_t^{kal} = E_{t-1}[\pi_t \mid \pi_{t-1}, MB_{t-1}, b_{t-1}, IP_{t-1}]$ 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 our fourth method (π_t^{ols}).

We use quarterly data over the post-World War II period (1948:Q1-2004:Q1). 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[9]. 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[10].

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[11]. 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 hypo-

9. 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).

10. Available at http://research.stlouisfed.org/fred2/

11. Results are available upon request.

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)
$[ep_t, \pi_t]$	**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)
$[ep_t, \pi_{t-1}]$	**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)
$[ep_t, \pi_t^{kal}]$	**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)
$[ep_t, \pi_t^{arima}]$	**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)
$[ep_t, \pi_t^{ols}]$	**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)
$[ep_t, tb_t]$	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.

thesis 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 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. Before investigate the role of these transitory movements in forecasting stock returns, 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 [12]:

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

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

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 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, we describe the data and provide summary statistics.

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

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. 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, $rrel$, 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 [13]. Following Lettau and Ludvigson (2001, 2005), we use the measure of short-term deviations from the long-run cointegration relationship among the natural logarithm of consumption (c), labor income (y) and aggregate wealth (a), henceforth $c\hat{a}y_t$. The aggregate stock market volatility, σ_t, is the non-conditional variance of the daily stock market return data adjust for the 1987 stock market crash [14]. Guo (2006) finds that this 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.

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13. Interest rate data come from the FRED II database.

14. The daily Dow Jones index was obtained from www.economagic.com. Following Campbell et al. (2001), Guo (2006) adjusts 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.

Table 2 shows basic summary statistics for the real stock return and the forecasting variables. Our 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 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 ($e\hat{p}i_t$) does not escape this rule.

Figure 1 plots the log earning-price inflation ratio and the real 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 real 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 real returns remain positive. This suggests that some non-linearities or structural break could occur in the underlying parameters governing this rela-

Table 2. – *Summary statistics.*

Correlation Matrix											
	r_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	0,23	0,26	0,05	–0,21	0,10	0,10	0,00	0,31	0,33	0,29
$e_t - p_t$		1,00	0,90	–0,28	0,08	0,38	–0,19	–0,13	0,25	0,69	0,79
$d_t - d_p$			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	–2.73	–3.43	–0.70	0.00	0.01	0.01	0.00	0.00	0.00	0.01
SD	0.08	0.39	0.39	0.18	0.01	0.00	0.01	0.00	0.01	0.32	0.34
Max	0.28	–1.92	–2.78	–0.27	0.05	0.03	0.04	0.00	0.03	0.83	0.82
Min	–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	0.97	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.

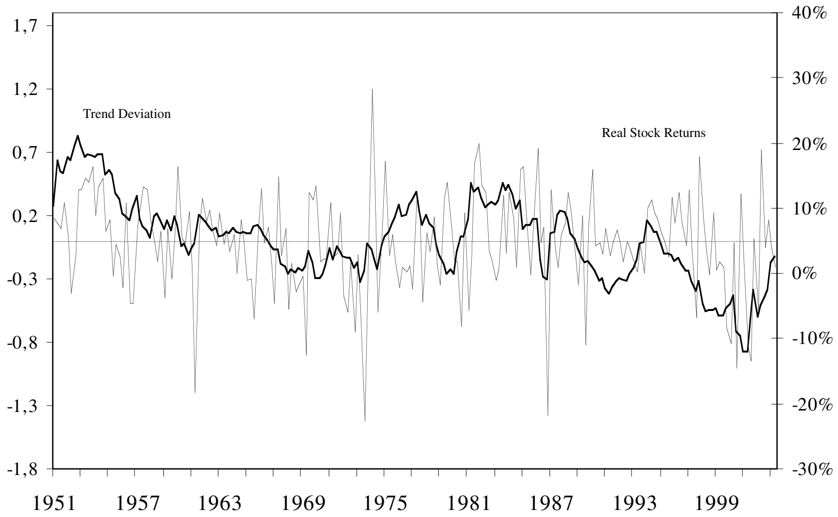

Figure 1. – *Real Stock Returns and transitory deviations from the common trend in the earning-price ratio and inflation.*

tionship or in the coefficient estimates of the cointegrating relation between the earning-price ratio and inflation. Nevertheless, theses episodes remain specific and transitory, as reflected in the subsequent continue downturn in real returns at the end of the 1990's.

5. Out-of-Sample Tests

In this section, we examine, the out-of-sample predictability of real stock returns. 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 in-sample forecasting results 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.

We consider two cases. 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. Second, the cointegration parameters are estimated recursively using only 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 [15].

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 $e\hat{p}i_t$. Thus the unrestricted model *nests* the benchmark "restricted" model. In the non-nested comparisons, we compare two competitor models. The Model 1 always uses just lagged $e\hat{p}i_t$ as a predictive variable; the Model 2 uses one (or two at more) of several alternate popular forecasting variables. All of the models include a constant.

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) [16]. We apply the *ENC-NEW* and *MSE-F* tests for the nested comparisons and the *MDM* test for the non-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 [17]. The *ENC-NEW* statistic provides a test of the null hypothesis that the restricted model

15. 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).

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

(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 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 [18].

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 $e\hat{p}i_t$.

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 of the sample.

We report results of the out-of-sample one-quarter-ahead nested forecast comparisons of real stock returns in Table 3. We consider two res-

17. 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.

18. The *ENC-NEW* and *MSE-F* statistics are explictly described in appendix.

tricted (benchmark) models: a model that includes only a constant as a predictor and a model that 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 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. Table 3 shows 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

Table 3. *One-Quarter-Ahead Forecasts of Real Returns: Nested Comparisons*

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

Note: The *MSE-F* statistic is used to test the null hypothesis that the MSE for the restricted model forecasts is less than or equal to the MSE for the unrestricted 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.

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 are shown in Table 4. 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 $e\hat{p}i_t$ the 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 [19].

In summary, the results presented indicate that $e\hat{p}i_t$ has displayed statistically significant out-of-sample predictive power for real stock 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 that forecasts using $e\hat{p}i_t$ would be consistently superior to forecasts using any other popular forecasting variables.

19. 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.

Table 4. – *One-Quarter-Ahead Forecasts of Real Returns: Non-nested Comparisons.*

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

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 $e\hat{p}i_t$ 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).

6. 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 graphical evidence of persistent deviations from the common trend in earning-price ratio and inflation (see Figure 1) suggests 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 for overlapping observations 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 [20]. 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.

Table 5 presents results of long-horizon regressions of real stock returns. First rows show that $e\hat{p}i_t$ has statistically significant forecasting power 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). 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).

20. The bootstrap procedure is described in details in Clark and McCracken (2004).

Table 5. – *Long-horizon Regressions of Real Stock Returns.*

		Forecast Horizon k								
#	Regressors	1	2	3	4	8	12	16	20	24
1	$ca\hat{y}_t$	**0.094**	**5.193**	**6.543**	**8.004**	**12.094**	**14.446**	**14.827**	**14.429**	**13.865**
		(4.555)	(4.822)	(5.320)	(5.684)	(5.329)	(5.560)	(5.041)	(4.569)	(3.431)
		[0.144]	[0.195]	[0.223]	[0.259]	[0.322]	[0.328]	[0.258]	[0.182]	[0.137]
2	$e\hat{p}i_t$	**0.143**	**0.200**	**0.254**	**0.303**	**0.505**	**0.659**	**0.695**	**0.671**	**0.637**
		(4.554)	(4.456)	(4.451)	(4.483)	(4.711)	(4.818)	(4.616)	(3.710)	(3.051)
		[0.159]	[0.199]	[0.230]	[0.253]	[0.353]	[0.383]	[0.337]	[0.238]	[0.179]
3	$e\hat{p}b_t$	**0.117**	**0.167**	**0.208**	**0.246**	**0.400**	**0.527**	**0.575**	**0.599**	**0.626**
		(3.615)	(3.662)	(3.605)	(3.600)	(3.890)	(4.263)	(4.326)	(4.046)	(3.699)
		[0.116]	[0.153]	[0.171]	[0.186]	[0.256]	[0.294]	[0.276]	[0.223]	[0.195]
5	$d_t - p_t$	**0.096**	**0.144**	**0.190**	**0.235**	**0.417**	**0.564**	**0.699**	**0.880**	**1.058**
		(3.251)	(3.432)	(3.598)	(3.750)	(4.743)	(5.764)	(6.953)	(8.232)	(8.526)
		[0.103]	[0.147]	[0.185]	[0.217]	[0.353]	[0.413]	[0.447]	[0.473]	[0.490]
6	$e_t - p_t$	**0.086**	**0.128**	**0.168**	**0.205**	**0.367**	**0.496**	**0.560**	**0.362**	**0.711**
		(3.027)	(3.203)	(3.346)	(3.450)	(3.965)	(4.088)	(4.188)	(4.067)	(4.056)
		[0.082]	[0.117]	[0.145]	[0.166]	[0.266]	[0.309]	[0.320]	[0.306]	[0.313]
7♦	$ca\hat{y}_t$	**0.067**	**4.071**	**5.203**	**6.415**	**9.868**	**11.153**	**11.126**	**12.091**	**13.905**
		(3.574)	(4.140)	(4.559)	(4.779)	(5.243)	(5.614)	(5.193)	(5.315)	(4.807)
	$e\hat{p}i_t$	**2.680**	**0.177**	**0.218**	**0.247**	**0.348**	**0.444**	**0.528**	**0.583**	**0.577**
		(4.249)	(4.008)	(3.921)	(3.783)	(4.006)	(4.735)	(5.400)	(4.115)	(3.442)
	$d_t - e_t$	–0.031	–0.040	–0.024	–0.008	0.047	0.062	0.234	**0.490**	**0.509**
		(–0.552)	(–0.527)	(–0.257)	(–0.071)	(0.336)	(0.402)	(1.237)	(2.061)	(1.705)
	$RREL_t$	–1.839	–2.723	–2.859	–2.811	0.690	3.709	**6.283**	**8.595**	**8.138**
		(–2.124)	(–2.204)	(–1.743)	(–1.555)	(0.388)	(1.686)	(2.376)	(3.181)	(2.677)
	DEF_t	1.303	1.534	2.490	3.795	7.583	**15.245**	**26.266**	**38.193**	**44.450**
		(0.632)	(0.546)	(0.700)	(0.903)	(1.325)	(2.729)	(3.567)	(4.566)	(5.028)
	TRM_t	–0.421	–0.907	–1.481	–1.821	–2.085	–0.046	2.517	2.150	–0.475
		(–0.492)	(–0.807)	(–1.066)	(–1.051)	(–0.844)	(–0.018)	(0.781)	(0.556)	(–0.115)
		[0.263]	[0.340]	[0.377]	[0.411]	[0.513]	[0.576]	[0.576]	[0.526]	[0.455]
8♦	$ca\hat{y}_t$	**2.798**	**4.208**	**5.397**	**6.676**	**10.234**	**11.409**	**10.951**	**11.632**	**13.897**
		(3.786)	(4.264)	(4.600)	(4.748)	(4.756)	(4.908)	(4.505)	(4.544)	(4.864)
	$e\hat{p}b_t$	**0.096**	**0.132**	**0.159**	**0.178**	**0.235**	**0.313**	**0.431**	**0.567**	0.669
		(2.519)	(2.516)	(2.444)	(2.358)	(2.474)	(3.138)	(4.244)	(4.907)	(5.336)
	$d_t - e_t$	–0.019	–0.023	–0.005	0.013	0.087	0.115	0.301	**0.598**	0.712
		(–0.312)	(–0.284)	(–0.050)	(0.114)	(0.553)	(0.674)	(1.545)	(2.813)	(3.220)
	$RREL_t$	–1.298	–1.987	–1.952	–1.770	2.293	**5.483**	**8.660**	**11.667**	**12.413**
		(–1.362)	(–1.443)	(–1.068)	(–0.867)	(1.108)	(2.119)	(3.079)	(4.784)	(4.685)
	DEF_t	1.147	1.317	2.252	3.534	7.612	15.044	**25.944**	**38.181**	**46.303**
		(0.476)	(0.406)	(0.540)	(0.712)	(1.081)	(1.927)	(2.672)	(3.910)	(4.725)
	TRM_t	–0.156	–0536	–1.009	–1.251	–1.042	1.377	4.450	**4.407**	**2.032**
		(–0.168)	(–0.426)	(–0.645)	(–0.632)	(–0.364)	(0.513)	(1.391)	(1.195)	(0.570)
		[0.211]	[0.283]	[0.311]	[0.346]	[0.437]	[0.501]	[0.527]	[0.532]	[0.503]

9♦	$ca\hat{y}_t$	**2.640**	**3.874**	**4.880**	**6.010**	**8.830**	**9.768**	**9.050**	**9.513**	**11.701**
		(3.266)	(3.619)	(3.817)	(3.893)	(3.909)	(3.886)	(3.311)	(3.524)	(4.556)
	$d_t - p_t$	**0.089**	**0.132**	**0.170**	**0.196**	**0.315**	**0.403**	**0.545**	**0.753**	**0.977**
		(2.262)	(2.479)	(2.567)	(2.554)	(3.289)	(3.695)	(5.240)	(6.434)	(9.426)
	$d_t - e_t$	–0.079	–0.113	–0.118	–0.117	–0.132	–0.162	–0.046	0.165	0.226
		(–1.249)	(–1.318)	(–1.152)	(–1.005)	(–0.836)	(–0.887)	(–0.225)	(0.791)	(1.122)
	$RREL_t$	**–1.970**	**–2.969**	–3.204	–3.219	–0.151	2.595	4.889	**6.685**	**6.996**
		(–2.023)	(–2.154)	(–1.791)	(–1.656)	(–0.073)	(1.069)	(1.788)	(2.557)	(2.802)
	DEF_t	–2.447	–4.068	–4.722	–4.533	–5.946	–2.086	3.188	7.547	8.018
		(–0.863)	(–1.128)	(–1.061)	(–0.852)	(–0.756)	(–0.257)	(0.345)	(0.794)	(0.866)
	TRM_t	0.236	0.099	–0.183	–0.305	0.351	3.117	**6.779**	**7.345**	6.132
		(0.248)	(0.077)	(–0.116)	(–0.154)	(0.127)	(1.170)	(2.076)	(2.106)	(1.844)
		[0.199]	[0.281]	[0.319]	[0.358]	[0.480]	[0.538]	[0.569]	[0.594]	[0.607]

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 6 presents *MSE-F* and *ENC-NEW* out-of-sample statistics. The p-values are generated using the bootstrap procedure. 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. 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.

7. 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-

Table 6. – *Long Horizon Forecasts of Real Stock Returns: Nested Models.*

k	1	2	3	4	8	12	16	20	24
				Panel A: 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
ENC-NEW	**8.498**	**13.388**	**16.054**	**17.298**	11.786	17.056	21.294	19.146	19.086
(p-value)	(0.001)	(0.004)	(0.007)	(0.012)	(0.078)	(0.069)	(0.066)	(0.091)	(0.099)
MSE-F	**8.704**	**14.960**	**20.625**	**22.686**	**17.206**	**24.855**	**25.555**	17.899	15.787
(p-value)	(0.000)	(0.001)	(0.002)	(0.004)	(0.027)	(0.024)	(0.034)	(0.062)	(0.081)
				Panel B: 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
ENC-NEW	**17.221**	**26.920**	**32.798**	**35.589**	**24.175**	**26.965**	26.811	19.425	11.454
(p-value)	(0.000)	(0.000)	(0.000)	(0.001)	(0.027)	(0.042)	(0.061)	(0.101)	(0.184)
MSE-F	**12.288**	**20.979**	**29.146**	**32.820**	**29.992**	**34.731**	**26.985**	12.361	0.828
(p-value)	(0.000)	(0.000)	(0.000)	(0.000)	(0.009)	(0.015)	(0.037)	(0.100)	(0.221)

Note: The *MSE-F* statistic is used to test the null hypothesis that the MSE for the restricted model forecasts is less than or equal to the MSE for the unrestricted 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 is the k-period log real stock returns. We estimate the cointegration parameters recursively in panel A and using the full sample in panel B. 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.

for-one with expected inflation because 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 investigate the role of these transitory deviations from this common trend for forecasting stock returns. We find that the deviations from the share trend in the earning-price ratio and inflation exhibit substantial out-of-sample forecasting abilities for real stock 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 inflation 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 inflation ratio fells sharply but real stock returns remain positive. Also, some recent works (*e.g*. Coakley and Fuertes, 2003; Bohl and Siklos, 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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Appendix: 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 ($1 \leqslant k$) 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 $\overline{d} = (P - k + 1)\sum_{t=R}^{T-k} \hat{d}_{t+k}$ $= MSE_1 - MSE_2$, 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 $u^2_{1,t+k}$ and $u^2_{2,t+k}$ 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:

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

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.