Dynamic asset allocation between stocks and bonds using the Bond-Equity Yield Ratio

Pierre Giot

Mikael Petitjean*

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ABSTRACT

We put forward the Bond-Equity Yield Ratio (BEYR) as a criterium to dynamically allocate capital between equities and bonds on a short-term basis. Relying upon 30 years of monthly data for a large collection of countries, we use the cointegration, regime-switching and ARMA-GARCH type methodologies to model and forecast the BEYR. While no model systematically beats the random walk from a statistical point of view, the out-of-sample forecasts show that the regime-switching model based on the forecasted probability generates the best and most consistent trading performance. A strategy based on the distribution percentiles is also consistent in its ability to outperform the buy-and-hold strategies. All in all, the BEYR is a remarkable relative market pricing tool in the US as it delivers higher risk-adjusted returns than the equity yield on a short-term basis.

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*Pierre Giot is Professor of Finance at the Department of Business Administration & CeReFiM (FUNDP, University of Namur) as well as CORE Research Member at Université Catholique de Louvain. Phone: +32 (0) 81 724887. Email: pierre.giot@fundp.ac.be. Mikael Petitjean is CIM-ICM Research Fellow at CeReFiM (FUNDP, University of Namur), Rempart de la Vierge, 8, 5000 Namur, Belgium. Phone: +32 (0) 81 724811. Send all correspondence to mikael.petitjean@fundp.ac.be. We gratefully acknowledge the helpful comments from participants at the 11th International Conference on Forecasting Financial Markets in Paris, the 10th International Conference on Computing in Economics and Finance in Amsterdam, the 9th Belgian Financial Research Forum in Brussels and the 2003 Symposium on Comparative European Applied Econometrics in Aix-Marseille. We also thank Dirk-Emma Baestaens, Renaud Beupain, Carine Brasseur, Chris Brooks, Christophe Dispas, Alain Durré, Peter Hansen, Sébastien Laurent and Andrew Patton for their excellent assistance and comments. The usual disclaimer applies.

1. Introduction

Although the efficient market hypothesis is widely regarded as a cornerstone of modern finance, the search for market-beating returns is still very much alive and still looks like the search for the Holy Grail of empirical finance.[1] A very large number of studies have indeed focused on whether financial variables can predict stock returns. Among the suggested variables or ratios, one can cite the consumption-wealth ratio (Lettau and Ludvigson, 2001), the equity share in total new equity and debt issues (Baker and Wurgler, 2000), Tobin's q (Robertson and Wright, 2004; Smithers and Wright, 2000), the dividend-payout ratio (Lamont, 1998), the book-to-market ratio (Kothari and Shanken, 1997; Pontiff and Schall, 1998), term and default spreads on bonds (Campbell, 1987; Fama and French, 1989), short-term interest rates (Ang and Bekaert, 2004; Campbell, 1987), and the well-scrutinized equity yield.[2]

Despite growing evidence that stock returns are somewhat predictable (Cochrane, 1999), sceptics, when confronted with this new body of evidence, point to problems of data mining, non-robustness of test statistics and incorrect inferences in small samples as causes of concern which cast doubt on these empirical results. They also stress that evidence of predictability is very much dependent on the investment horizon. While most studies using long-horizon returns show evidence of a certain amount of predictability, findings based on short-horizon returns usually indicate the opposite (e.g. Xia, 2001). In most empirical studies, the extent of return predictability is also often assessed from a statistical perspective, with the t-statistic and R^2 of in-sample predictive regressions guiding conclusions. However, statistical evidence of predictability using in-sample predictive regressions does not necessarily imply economic significance based on out-of-sample forecasts (Boudry and Gray, 2003). Finally, much of the evidence of predictability has been found in a static framework, with few attempts to dynamically time the market.

The focus of this study deals with the issue of short-term market timing between stocks and long-term government bonds and whether we can put forward dynamical trading strategies that lead to superior out-of-sample forecasts. Regarding the criteria used to switch between equities and bonds on a short-term basis, we suggest the modelling of the Bond-Equity Yield

[1] After being wiped out in one of the many stock market crashes of his era, Isaac Newton already wrote in 1768: "I can calculate the motions of the heavenly bodies but not the movements of the stock market".

[2] Key papers on the equity yield include Basu (1977, 1983), Campbell and Shiller (1988a, 1988b, 1998, 2001), Fama and French (1988, 1989, 1992), Hodrick (1992), Jaffe, Keim, and Westerfield (1989), Rozeff (1984), and Shiller (1989).

Ratio (BEYR), which is defined as the ratio of the bond market income yield to the stock market income yield. In our framework, the bond market income yield is the yield-to-maturity on long-term government bonds. The stock market income yield is the equity yield of the most representative stock market index. In the empirical application, the equity yield is successively proxied by the earnings yield and the dividend yield.

For a large number of countries and over a period spanning more than 30 years (monthly data), we first assess, from an in-sample point of view, the relationship between equity yields and long-term bond yields in a cointegrating framework. In the core of the paper, we then carry out out-of-sample forecasts based on the cointegration methodology in an attempt to time the market: when the forecasts predict that equities will underperform (outperform) long-term bonds during the following month, we shift funds out of stocks (bonds) into bonds (stocks). Secondly, we use the Markov switching regime methodology (which captures the salient statistical and distributional features of the BEYR) and ARMA-GARCH type methodologies to model the BEYR ratio and deliver out-of-sample forecasts on which the same trading rules can be based. Thirdly, we provide a rigorous statistical evaluation of these out-of-sample forecasts by including equally and superior predictive ability tests. Fourthly, we carry out a dynamic allocation exercise where we measure and compare the trading profitability of naive specifications (which rely exclusively on past information) with the cointegration, regime-switching and ARMA-type models. Finally, we check whether the BEYR delivers higher trading profitability than the equity yield on a short-term basis.

The rest of the paper is structured as follows. Section 2 discusses the relationship between between equity and bond yields. We present the dataset in Section 3. The cointegration and regime-switching econometric frameworks are detailed in Section 4. We also explain how the out-of-sample forecasts of the BEYR are evaluated from the statistical and trading perspectives. We discuss the empirical results in Section 5 and concludes in Section 6.

2. Earnings, dividends, stock prices and bond yields

2.1. Stock prices and bond yields

As the core of our approach focuses on the comparison of appropriately defined stock and bond yields, we first review how the discount rate and cash-flow effects shape the relationship between stocks and bonds. In the well-known Gordon (1962) model, the 'fundamental' stock price of a security is:

$$P_t = \frac{D_{t+1}}{K_e - g} = \frac{kE_{t+1}}{r_f + \pi - g} \tag{1}$$

where D_{t+1} is the expected dividend one year from now, k is the payout ratio, E_{t+1} is the expected earnings, K_e is the cost of equity (or equivalently the return demanded by the stockholders to buy the stock), g is the expected long-term earnings growth rate, π is the risk premium demanded by investors to hold the stock, and r_f is the 'risk-free' rate. In theory, r_f reflects the short-term interest rates that will prevail in the future. Since these rates are not observable, the current long-term yield is generally used as a proxy.

The discount rate effect acts through the cost of equity (K_e). Because K_e heavily depends on the prevailing interest rate, rising (falling) bond yields should mechanically lead to lower (higher) stock prices. Hence, the discount rate effect suggests a negative correlation between stock prices and bond yields (provided that variations in the required risk premium do *not* offset the bond yield changes). As to the cash-flow effect, it operates through the expected long-term earnings growth rate (g). A positive (negative) cash flow effect comes from an upward (downward) revision in earnings growth and leads to a stock price appreciation (depreciation). In contrast to the discount rate, the cash flow effect generally points to a positive correlation between stock prices and bond yields as most of the upward (downward) earnings revisions occur in upturn (downturn) economic cycles when interest rates are rising (falling). Unfortunately, it is hard to argue that the discount rate and cash-flow effects are independent. The overall picture is further complicated by a possibly time-varying (at least on a short-term basis) risk premium and the so-called monetary illusion effects brought about by the dynamics of inflation.

Not surprisingly, little consensus has emerged in the literature focusing on the relationship between stock prices and bond yields. For example, using a dynamic present value model and a long sample of annual U.S. data, Beltratti and Shiller (1992) report strong negative correlation between stock prices and long-term bond yields. Using a more recent sample of monthly stock and bond returns, Ammer and Campbell (1993) document a relatively low negative average correlation. While most of the studies in the 1990's implicitly assume constant covariance structures, much of the subsequent empirical literature has relaxed this potentially binding constraint and dealt with time-varying stock and bond co-movements. For example, the discount rate effect should be more important during expansions while the cash flow effect should dominate during contractions (Boyd, Jagannathan, and Hu, 2001; Andersen, Bollerslev, Diebold, and Vega, 2003). This gives rise to negatively correlated stock prices and bond yields in expansions and higher, perhaps positive, correlations during contractions. The concept of state-dependency in stock and bond co-movements was first theoretically developed by Barsky (1989). Further theoretical arguments and empirical evidence are given in Fleming, Kirby, and Ostdiek (1998), David and Veronesi (2004), Li (2002), Ribeiro and Veronesi (2002), Rigobon and Sack (2003, 2004), Guidolin and Timmermann (2003), Scruggs and Glabadanidis (2003) and Connolly, Stivers, and Sun (2004), among others. The risk premium demanded by investors also varies with the state of the economy. It usually decreases during upturn economic cycles and increases during downturn economic cycles. Therefore, the risk premium effect decreases the correlation between stock and bond prices, both at economic peaks and troughs. It is nevertheless difficult to predict how this correlation will evolve between peaks and troughs, as the stock market responses to economic news tend to be asymmetric across the business cycle (McQueen and Roley, 1993).

2.2. The Bond-Equity Yield Ratio (BEYR)

As the relationship between stock prices and bond yields can be subject to competing interpretations, it is unrealistic to think that market participants can profitably allocate financial resources between equities and long-term bonds by simply comparing their prices. The active comparison of the respective bond and stock market income yields is instead a market timing strategy much favored by practitioners. To engage in such an operation, market participants believe that a 'substitution effect' between stocks and bonds is in play and that such an effect is shaped by the relationship between equity and bond yields. For example, Mills (1991) applies this strategy to forecast a stock index future performance. He suggests a cointegration framework to model a stock price index, an associated dividend index and a long-term government bond yield. The long-term Bond-Equity Yield Ratio (BEYR) approach developed in this paper is a very similar concept.[3] The BEYR is defined as the ratio of the yield on long-term government bonds to the dividend yield on the stock index. Proponents of the BEYR approach (or GEYR approach in the UK) argue that the BEYR fluctuates around a central value, and that any deviation from this 'long-term value' indicates that the stock market is underpriced or overpriced with respect to the bond market. In other words, the current BEYR should have predictive power for forecasting future stock index returns (e.g. Levin and Wright, 1998, and Harris and Sanchez-Valle, 2000a and 2000b).

In the traditional formulation of the BEYR, the dividend yield, instead of the earnings yield, is used as a proxy for the income yield of the stock market. This is justified on the grounds that cash dividends are unambiguous while earnings are not. [4] However, dividend payout policies are strongly sensitive to regulatory and taxation changes. For example, since the 1982 corporate policy upheaval in the US, dividend payout ratios have been decreasing from around 55% to about 35%. Dividend yields fell even faster as stock prices soared over the past two decades.[5] To reflect the importance of both dividends and earnings, we consider two versions of the BEYR ratio in our empirical analysis. In the first case, the BEYR ratio takes the dividends as inputs (the equity yield is thus the dividend yield), while it features the earnings in the alternative specification (the equity yield is the earnings yield).

Although the direct comparison of equity yields ('real' variables) and long-term bond yields ('nominal' variables) is theoretically erroneous, market practitioners view such a ratio as a valuable short-term trading tool. In this approach, investors would set the market's earnings yield as a function of inflation and nominal interest rates. For example, the investors' taste for equity risk changes with the level of inflation. When inflation is high, investors (possibly wrongly) demand a higher risk premium, higher expected stock returns and thus a higher equity yield. This is mostly true when monetary policy actions targeting current strong in-

[3] In the UK, this ratio is better known as the Gilt-Equity Yield Ratio (GEYR).

[4] Earnings are prone to balance-sheet and income statements embellishments. For example, depreciation expenses are based on book values and can be very crude approximations of the actual reduction in economic value of physical plant and equipment. Corporate pension plan accounting are also known to affect pre-tax profits. Besides, the pressure to meet short-term earnings expectations may lead CEOs to employ accounting devices whose sole purpose is to obscure potential adverse results. In contrast, the discipline of dividend payments reduces the incentive for the management to boost earnings by using tricks and accounting gimmicks.

[5] Dividend yields decreased from 6% in the 1950's to barely above 1% today. Recent tax code changes in the US could however favor once again dividend payments.

flation are interpreted by investors as leading to stronger instability in the future. The direct comparison of bond and earnings yields would therefore make sense on a practical short-term basis. An example of such model is the so-called "Fed's Stock Valuation Model" which states that the 10-year government bond yield should be inversely related to the expected earnings yield of the S&P500 index. The Fed model framework is similar to the BEYR framework, but with the equity yield proxied by the anticipated earnings yield. The underpinnings of the Fed model also include the substitution effect between stock and bonds and is loosely based on classical dividend valuation models. In practice, the Fed model suggests asset allocation decisions based on the perceived degree of over and underpricing of the S&P500 with respect to its fair value.[6] Recently, similar models have been suggested in the literature on empirical asset pricing. For example, Lander, Orphanides, and Douvogiannis (1997) put forward a model that takes into account anticipated earnings yields and bond yields to forecast future equity returns on the S&P 500 index. Pesaran and Timmermann (1995) include both interest rates and equity yields as possible explanatory variables of stock market movements. Shen (2003) uses the spread between the earnings yield and prevailing interest rates to time the market.

3. Data

Our dataset includes the dividend and earnings yields for selected stock indices, the stock price indexes by themselves as well as the income yields for selected government bonds on a monthly basis. Six countries are available: France, Germany, Japan, The Netherlands, the UK and the US. The time period ranges from January 1973 to January 2004, yielding a total of 373 observations.[7] This is a longer time span than what is usually available in the related literature, taking into account the fact that we conduct an international analysis (most studies focus on UK or US data only). The stock market indices are the Datastream global equity indices, whose constituents cover at least 75% to 80% of the total market capitalization of each country. The dividend yield and the price-earnings ratio (which gives the earnings yield) of these indexes are also available from Datastream. The bond yields are the Datastream long-term government bond yields, which have been available since 1957 for the major markets.

[6] Recent modifications of the Fed model include the "Stock Valuation Models #2" (SVM-2) introduced by Yardeni (2003). See also Durré and Giot (2004) for a discussion of the Fed model.

[7] Note that expected earnings were not available for that extended time frame. We thus use the reported earnings and dividends.

Finally, we use the Datastream total return indices on 10-year government bonds to track the performance of long-term bonds.

For each country, we plot the time path of the BEYR ratios in Figures 1 and 2. These ratios display large up and down swings and are large on an absolute basis at local stock market peaks. For example, the US stock market bubble seems to materialize in less than a year, from the late 1998 to the mid 1999. In the early 2000, the US BEYR series reach their all time high, far above their previous 1987 peaks. With the benefit of hindsight, the US equity market looked incredibly overpriced in 2000, the more so if we look at the ratio of the bond yield to dividend yield. Interestingly, the UK BEYR series are poorly correlated with the US BEYR series and did not appear to be 'overpriced' in 2000 (at least compared to 1987). The Dutch BEYR series exhibit the same kind of behavior as the US series. These two countries appear to be the most correlated within the sample.[8] The peak of Japan's bubble in 1990 can also be easily identified. This country features both the highest and lowest values of the BEYR among the countries included in the sample (see Table I). For France, equities in 1987 appeared to be more overpriced (relative to the bond market) than in the early 2000.

According to the Bera-Jarque normality test statistics, we reject the hypothesis of normality for all BEYR series except for the bond-earnings yield ratio in the US. Moreover, the BEYR series are autocorrelated as the Ljung box Q^* statistic rejects the null of no autocorrelation in all cases. Engle's LM test for autoregressive conditional heteroscedasticity indicates that the BEYR variances are time-varying. Brooks and Persand (2001) note that these statistical results motivate the use of a model featuring time-varying components (for the mean and/or the variance). The unconditional distribution of the BEYR series confirm that the BEYR is far from being normally distributed: the BEYR series often display significant bumps in their tails, which suggests distinct regimes.[9] This motivates the use of a two-regime switching model, tailored to take into account the low and high BEYR regimes, such as used later in the analysis.

[8]The correlation matrices of the BEYR are not reported to save space. They are available from the authors upon request.

[9]These figures are available from the authors upon request.

4. Methodology

As the market practitioners' actions as well as the literature review of Section 2 hint at a possible long-term stable relationship between bond and equity yields, we first model the BEYR series by relying upon the cointegration framework. In a second step, we use the Markov switching regime methodology as it has been shown to appropriately capture both the statistical and distributional features of the BEYR (Brooks and Persand, 2001). Finally we present the ARMA-GARCH type models used to model the BEYR. In the out-of-sample forecasting exercise detailed in the last sub-section, all three methodologies deliver BEYR forecasts upon which the trading rules are based.

4.1. Cointegration models

In most papers, there is no prior test for cointegration between the variables (namely, the stock price index, the earnings or dividend index, and the long-term bond yield). The econometric relationship between the variables is directly specified as a linear combination and the ordinary least squares regression is traditionally used to estimate the model (Asness, 2003). In other studies, the cointegration is used, but without taking the bond yield as an input. For example, Campbell and Shiller (1987) do not get meaningful cointegration results between stock prices and dividends, while MacDonald and Power (1995) validate the present value relationship between earnings and stock prices for the US market. Although Harasty and Roulet (2000) add the 10-year bond yield as an input in their model, they use the 2-step Engle-Granger methodology so that their cointegrated model is reduced to a single equation and there are no statistical tests on the coefficients of the long-term model relationship. In our cointegration framework, we test for cointegration between either r_t, e_t and p_t or r_t, d_t and p_t, where $r_t = ln(R_t)$ is the log long-term government bond yield, $e_t = ln(E_t)$ is the log earnings index, $d_t = ln(D_t)$ is the log dividend index and $p_t = ln(P_t)$ is the log stock index for which the earnings and dividends are available. If there is a valid long-term relationship between the constituents of the BEYR, we proceed with the cointegrated VAR modelling.

The first step of our cointegration analysis involves order of integration tests for each variable taken as input. Six unit root tests have been used to overcome the potential problem exhibited by unit root tests, that is, their poor size and power properties due to the near equivalence of non-stationarity and stationary processes in finite samples. The following unit root tests are used: the Augmented Dickey-Fuller (ADF), Philipps-Perron (PP), Dickey-Fuller GLS de-trended (DFGLS), Elliott-Rothenberg-Stock Point-Optimal (ERSPO), Ng and Perron (NP) and Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) tests. These tests are applied to the log of the variables as well as to their first and second differences (to check for the presence of an order of integration higher than 1). We also compute the test statistics without the constant and trend. Finally, we use the Dickey and Pantula (1987) approach to check whether this methodology leads to different conclusions regarding the non-stationarity of the variables.

The second step requires cointegration tests of the Johansen type, where we have to set the appropriate lag length of the multivariate model. The number of lags (k^*) is determined such that the last included $k^* + 1$ lagged variables in the VAR specification are jointly non significant. Moreover, we compute the classical univariate and multivariate diagnostic tests and look at the AIC, SC and HQ criteria. When the information criteria suggest different values of k^*, we rely on the HQ criterion (Johansen, Mosconi, and Nielsen, 2000). Finally, we carry out model reduction tests to check the parsimonious feature of the model. The question of whether deterministic variables should enter the cointegration space is addressed after testing for the number of cointegration vectors. To test for cointegration rank, we use the trace statistic as the sequence of trace tests leads to a consistent testing procedure.

Because the d_t, e_t and p_t series exhibit a positive drift (detailed figures are available upon request), the so-called Model 3 of cointegration (that is, a model with an unrestricted constant and no trend) seems warranted. Besides Model 3, testing for rank order is also undertaken under two alternatives. The first alternative includes a restricted intercept (Model 2) while the second alternative includes both an unrestricted constant and a restricted trend (Model 4). Although plots of the data in levels (and first differences) help choose the most appropriate model, they sometimes provide little objective information. For example, it is very difficult to tell when Model 4 should be used, since this model is selected when the available data cannot account for other unmeasured factors that induce autonomous growth in the variables. On the other hand, variables like bond yields, which do not drift upward or downward over time, might also require the intercept to be restricted to lie in the cointegration space (Model 2). Johansen (1992) suggests the use of the so-called Pantula principle to test the joint hypothesis of both the rank order and the deterministic components. We therefore estimate all three models and present the results from the most restrictive alternative (i.e $c = 0$ and Model 2) through the least restrictive alternative (i.e. $c = n-1$ and Model 4).[10] The test procedure requires that we look at all models (Models 2, 3 and 4), successively compare the trace test statistic to its critical value, and stop the first time the null hypothesis is not rejected.

When the variables for a given country are indeed cointegrated, we estimate the ECM-VAR(k^*) model to assess the short-run and long-term dynamics of the system. Let us illustrate the methodology when the earnings are taken as inputs. If there is one cointegration relationship between the three variables and if the constant is unrestricted, the VAR-ECM(k^*) can be written as:

$$\Delta e_t = \gamma_e + \alpha_e(e_{t-1} + \beta_p p_{t-1} + \beta_r r_{t-1}) + \text{Short-run dynamics} \quad (2)$$

$$\Delta p_t = \gamma_p + \alpha_p(e_{t-1} + \beta_p p_{t-1} + \beta_r r_{t-1}) + \text{Short-run dynamics} \quad (3)$$

$$\Delta r_t = \gamma_r + \alpha_r(e_{t-1} + \beta_p p_{t-1} + \beta_r r_{t-1}) + \text{Short-run dynamics} \quad (4)$$

Note that this is Model 3 as we do not constrain the constant to be in the cointegration relationship. In contrast to Campbell and Shiller (1987) and MacDonald and Power (1995), we include the long-term bond yield in the equilibrium relationship. If the economic rationale underpinning the BEYR framework is correct, the coefficients of the long-run relationship (i.e. β_p and β_r) are expected to be negative. As to the adjustment speed coefficients (i.e. α_e, α_p and α_r), they determine how each variable is affected by the disequilibrium in the lagged long-run relationship.[11] Let us first look at the sign of α_p in Equation 3. If earnings increase (decrease) and bond yields decrease (increase), which implies a positive (negative) disequilibrium in the cointegration vector, we would logically expect positive (negative) stock index returns. Hence, α_p should be positive. Note that this will be verified only if the adjustment dynamics operating through the stock index variable over the next month is sufficiently strong. By the same token, α_e is expected to be negative, should the equilibrium be restored over the next period. If there is a positive (negative) disequilibrium in the cointegration vector, we would expect earnings to decrease (increase) over the next period. For example, if bond yields start falling in such a way that the BEYR also decreases (i.e., $e_{t-1} + \beta_p p_{t-1} > |\beta_r r_{t-1}|$), we would expect earnings yields to adjust through a fall in earnings. Correspondingly, one expect α_r to be positive. For example, let us assume that the earnings yield starts increasing in such a way that the BEYR

[10] c is the rank of the long-run coefficient matrix while n is the number of variables included in the cointegration analysis.

[11] Because the variables are expressed in logs, the adjustment speeds can also be interpreted as the proportion of the long-run disequilibrium error that is corrected at each time step.

falls. If some kind of long-term binding relationship exists between earnings and bond yields, the latter will start rising relatively to the former at some point in the future.

In the subsequent empirical study, we focus on the short-term out-of-sample forecasting performance of this cointegration model as we decide to allocate capital between stocks and long-term bonds on a monthly basis. In that out-of-sample forecasting framework, 1-month ahead forecasts for e (or d), p and r are recombined to deliver BEYR forecasts upon which the trading rules are based.

4.2. Regime switching modelling

In the preceding section, we looked at the BEYR in a multivariate framework by focusing on its constituents. The alternative, à la Brooks and Persand (2001), is to model the BEYR in an univariate framework through regime switching models. These models are particularly appropriate for modelling the BEYR as the restrictive assumptions of normality, constant mean and variance are not relied upon. In the class of models that let regimes be determined by unobservable variables, the Markov switching (MS) model advocated by Hamilton (1989) is the most popular. In such a model, the regime occurring at time t cannot be observed as it is determined by an unobservable first-order Markov-process s_t. This implies that the current regime s_t only depends on the past regime s_{t-1}. Focusing on the two-regime case, the transition probabilities are defined by:

$$P(s_t = 1|s_{t-1} = 1) = p_{11}, \tag{5}$$

$$P(s_t = 2|s_{t-1} = 1) = p_{12}, \tag{6}$$

$$P(s_t = 1|s_{t-1} = 2) = p_{21}, \tag{7}$$

$$P(s_t = 2|s_{t-1} = 2) = p_{22}. \tag{8}$$

The selected MS model in this paper follows the MSIAH specification with regime-dependent intercept and heteroscedasticity, as defined in the Krolzig's (1997) MSVAR Ox package. In the subsequent out-of-sample forecasting exercise, we use the Markov switching methodology to forecast the value of the BEYR and the forecasted probability of switching, both of which will be relevant inputs in the trading rules. Thus the cointegration framework and the MS methodology share the same logic: both deliver 1-month forecasts for the BEYR which are fed into the trading rules described below. Note however that, in contrast to the MS model which delivers an univariate forecast, the cointegration model delivers forecasts for the BEYR constituents which must be 'put together' to reconstruct the forecasted BEYR.

4.3. ARMA-GARCH type models

Among the class of univariate models, we also consider a number of popular competing models which range from naive BEYR models to rather sophisticated ARCH-type models. These competing models are: the random walk (RW), AR(k), ARMA(k,l), ARMA(k,l) - GARCH(p,q), ARMA(k,l) - EGARCH(p,q), ARMA(k,l) - TGARCH(p,q), ARMA(k,l) - PGARCH(p,q), and ARMA(k,l) - CGARCH(p,q) where k,l,p and q are determined by in-sample minimization of information criteria.[12] We do not detail these models since they have been widely popularized over the last 15 years and are now 'textbook' econometrics.[13] In the empirical study, we compute the out-of-sample one-step ahead BEYR forecasts for each of the aforementioned models, using a rolling window and re-estimating the model accordingly.

4.4. Out-of-sample forecasting

As the trading strategies used to dynamically allocate capital between equities and bonds depend on the level of the BEYR, we perform out-of-sample forecasts of the BEYR *itself*. We first assess the forecasting accuracy of the competing models in a pure statistical evaluation framework. In the second part of the out-of-sample exercise, we define four trading rules used to compare the trading profitability of the models. Finally, we check which of the BEYR and the equity yield (i.e. without modelling the long-term government bond yield) generates the highest short-term trading performance.

4.4.1. Statistical evaluation of the BEYR forecasts

For each model, the rolling-regression BEYR forecasts are assessed using the following criteria: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Median Squared Error

[12] We select the most parsimonious model among the 'best' models selected by the Akaike, Schwarz and Hannan-Quinn information criteria.

[13] Excellent reviews of ARCH-type models are given in Bollerslev, Engle, and Nelson (1994), Diebold and Lopez (1995), Palm (1996) and Granger and Poon (2003).

(MedSE), Mean Absolute Error (MAE) and Median Absolute Error (MedAE). We also compute the direction accuracy (DA) of each model, i.e. the percentage of correct predictions in direction changes. This highlights the market-timing ability of a model as we compare the signs of the model forecasts with the signs of the realizations. We then report the P-value of Pesaran and Timmermann (1992) (PT) nonparametric test. Under the null hypothesis of this test, there is no statistical evidence of model market-timing ability. According to the alternative hypothesis, the percentage of correct predictions in direction changes is significantly greater than 50%. Since the RW has no market timing ability by definition, no DA and PT is reported for the RW model.

To test whether the forecasts from *two* models are equally accurate, we first use the modified Diebold and Mariano (MDM) test.[14] Under the null hypothesis of equal predictive accuracy (EPA), there is no significant difference between the mean of the squared forecast errors of the two models. The alternative hypothesis is that the benchmark model outperforms the competing model. The MDM test is commonly regarded as one of the best diagnostic measures. For example, Clements, Franses, Smith, and van Dijk (2003) find that the MDM statistic is more powerful in discriminating linear and nonlinear models than techniques based on interval or density forecasts, as developed by Christoffersen (1998), Diebold, Gunther, and Tay (1998), Berkowitz (2001) and Bauwens, Giot, Grammig, and Veredas (2004). The truncation lag is set according to Andrews (1991) AR(1) automatic selection procedure to determine the number of lags.[15] The nonparametric sign test is an alternative method to test whether the forecasts from two models are equally accurate. The null hypothesis is a zero-median loss differential, while the alternative hypothesis is that the benchmark model outperforms the competing model. This test does not rest on the restrictive assumptions that the forecast errors are free of serial correlation, normally distributed and not contemporaneously correlated. It therefore retains good size in the presence of non-normality, serial and contemporaneous

[14]The Diebold and Mariano statistic was modified by Harvey, Leybourne, and Newbold (1997) to account for potential finite-sample size distortions. The statistical distribution of the MDM test statistic is the t-student distribution.

[15]We have also used two fixed lags (0 and 12) to estimate the spectral density at frequency zero as well as the following well-known rule of thumb,

$$L = floor[(\frac{4T}{100})exp(2/9)], \tag{9}$$

where L is the number of lags and T is the number of out-of-sample forecasts. We do not report these results since they are similar to those using Andrews' technique. They are available from the authors upon request.

correlation (Lehmann, 1998).[16] In the aforementioned EPA tests, we always benchmark the competing models with respect to the random walk.

We finally test whether each particular forecasting model is outperformed by the other alternative models using Hansen's (2004) test for superior predictive ability (SPA). The null hypothesis is that the model under scrutiny is not inferior to any of the other competing models.[17] A low *P*-value indicates that the model is inferior to one or more of the competing models. A high *P*-value shows that the model under test is not outperformed by any of the competing models. The SPA *P*-value takes the space of models into account. That is, it does not ignore the model selection procedure that preceded the choice of the competing models. Whereas the framework of Diebold and Mariano (1995) involves test for EPA, the testing problem in Hansen's framework is a test for SPA. The former leads to a simple null hypothesis, whereas the latter involves a composite hypothesis. The usual way of handling the ambiguity of a composite hypothesis is to use the least favorable configuration (LFC) as in White's (2000) reality check for data snooping. However, this makes the test sensitive to the inclusion of poor and irrelevant forecasting models. As Hansen's SPA test does not rely on the LFC, it is argued to be more powerful than White's.[18]

In the following sub-section, we measure the profitability of trading rules based on the BEYR. To alleviate the potential data snooping problem, we only consider forecasting models for which the null hypothesis of the SPA test is not rejected at the 5% level. Provided that the cointegration and MS models pass the SPA test, we compare the profitability of these two models with the trading performance of the 'statistically best performing' (SBP) model. The SBP model is defined as the forecasting model (excluding the random walk) that gets the best average ranking regarding the accuracy metrics *and* for which the null hypotheses of the MDM, Sign and SPA tests are not rejected at the 5% confidence level. An interesting issue is to check whether the SBP model performs as well in the dynamical allocation exercise.

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[16] We have also computed the *P*-values of the following EPA tests: Wilcoxon's signed-rank test (SR), simple *F* test (F), Morgan-Granger-Newbold test (MGN), Meese-Rogoff test (MR) and Mizrach test (M). We do not report these results since they are broadly in line with the MDM and sign tests.

[17] We use the mean squared error metric as the loss function. The dependence parameter is set to 0.5 and the number of re-samples is equal to 10,000.

[18] Dr. Peter R. Hansen of Stanford University has compiled an Ox computer code for implementing the SPA test. The implementation is based on the stationary bootstrap but the block bootstrap can also be adopted.

4.4.2. Economic evaluation of the BEYR forecasts

The trading philosophy consists in shifting funds out of stocks and into long-term government bonds when the BEYR is predicted to be overpriced relative to its 'fair value' or to some threshold. That is, when the equity yield is abnormally smaller than the prevailing bond yield. Correspondingly, we shift funds out of long-term government bonds and into stocks when the equity yield is considered to be abnormally larger than the prevailing bond yield. Note that this can be a somewhat loose comparison, which is shaped by the trading strategy in use. A practical implementation of this procedure would include buying and selling stock index and bond futures.

Trading profitability is measured in the following ways. We first follow a trading rule for which the threshold value of the BEYR is given by the random walk model (strategy I). Assuming that stock markets are efficient, the most consistent forecast should indeed be the random walk. According to the random walk, the forecast is equal to the last-known observation. Short term deviations from the random walk forecast are likely, but they should result from temporary market inefficiencies. Any BEYR forecast that is larger (lower) than the last observation indicates that equities are being priced relatively to bonds at a higher (lower) level than the random walk would imply: the trading rule consists in selling (buying) equities and buying (selling) bonds. The second strategy compares the model forecasts with different proxies for the 'fair value' of the BEYR, namely the long-term unconditional mean (strategy IIA), the short-term 1-year conditional mean (strategy IIB) and the forecasted cointegrating value (strategy IIC). When the model forecast is higher (lower) than this 'fair value', we sell (buy) equities and buy (sell) bonds. We also follow a naive approach that exclusively relies upon past information. As no attempt is made to forecast the BEYR, we just compare the last observation with the fair value. Again, we sell (buy) equities and buy (sell) bonds if the last observation is higher (lower) than the fair value.

While the strategies detailed above depend on the definition and measurement of some kind of 'fair value', we also consider an alternative setting where extreme values of the BEYR could provide useful information for timing the market (strategy III). This strategy is meant to identify the months when the stock market seems so pricey that investors may be better off avoid it. When the BEYR is above an appropriately defined threshold, it is interpreted as a signal according to which market downturns are likely to be witnessed in the next month.

Extremely high values of the BEYR indeed signal a higher probability of imminent market downturns. We use the 90th percentile of the historical range of the BEYR to define the threshold of the 'extremely high BEYR', and interpret it as predicting a market downturn in the next month (Shen, 2003). The choice of the 90th percentile as the threshold implicitly assumes that the stock market moves 10% of the time far away from its fundamental value. This is consistent with Black's (1986) estimation. As long as the forecast is lower than the 90th percentile value, we stay into stocks. We also implement a naive version of this strategy whereby the last observation (instead of the forecast value) is compared to the 90th percentile.

The next step involves taking into account the information provided by the MS methodology. That is, we base our trading strategy on the forecasted *probability* of the BEYR to be in the low regime during the next period (strategy IV). In this case, the trading rule involves selling (buying) bonds and buying (selling) equities when the probability of being in the low regime is forecast to be greater (smaller) than a predefined threshold. Although we first consider the 0.5 threshold, we also use a 0.9 threshold to check whether switching decisions based on a higher degree of certainty about the forecasted regime lead to higher trading profitability. As the equity yield has been found in the literature to exhibit rather strong predictive ability, we also drop the bond yield variable and use the same trading rules in order to check whether higher trading performance is achieved by relying upon the equity yield alone. In this simplified setting, we keep the same forecasting models than those previously used to measure the profitability of trading rules based on the BEYR.

The rolling estimation is implemented as follows. Once the forecast is computed, the estimation of the model is rolled forward one month, with a new set of estimated model parameters. This process goes on until the end of our sample (January 2004) is reached. The returns for all out-of-sample months for the switching portfolio are computed, and their characteristics compared with those of buy-and-hold equities and buy-and-hold long-term bonds strategies. Returns are calculated as continuously compounded percentage return on a stock index and on a long-term government bond portfolio. Transaction costs are evaluated following Sutcliffe (1997) estimates.[19] According to Sutcliffe (1997), an appropriate round-trip figure for the FTSE-100 futures is 0.116% (of the purchase and sale values). This figure is made up of bid/ask spread (0.083%) and commissions (0.033%). To keep things simple, we

[19] As market participants can easily replicate the above strategies by trading the corresponding bond and stock market futures contracts, we consider transaction costs on the futures markets.

assume identical costs for the two markets. These are very conservative estimates. For example, using JP Morgan for execution and settlement, a typical European bank pays per trade 1.88$ and 2.85$ per 100,000$ contract value on CBOT stock index and fixed income futures respectively. Transaction costs are even lower on Eurex fixed income futures such as the Schatz, Bobl and Bund futures. The transaction cost is 1.05 EUR per trade and per contract value of 100,000 EUR.

5. Empirical analysis

5.1. Cointegration analysis

Among the econometric models presented above, the cointegration approach deserves a special preliminary treatment prior to the out-of-sample empirical analysis. Indeed, this model hinges on stronger assumptions for the BEYR constituents than the other approaches and it also models these BEYR constituents in a truly multivariate framework. For example, the cointegration poses the following questions, which should first be addressed: Are the earnings, dividend and stock price indexes integrated of order one? Is the long-term government bond yield also integrated of order one? Are the BEYR constituents (either the earnings, stock price indexes and long-term government bond yield, or the dividend, stock price indexes and long-term government bond yield) cointegrated? If they are indeed cointegrated, what ECM-VAR model should be put forward? To address these issues, the cointegration analysis is carried out in the following order: unit root tests, lag length determination, cointegration tests and ECM-VAR(k) model specification and estimation. Note that this analysis is carried out on the whole sample, but we also ascertained that we concluded similarly when a smaller sample (required for the start of the out-of-sample analysis) was used.

5.1.1. Unit root tests

According to the results of Tables II and III, all BEYR constituents seem to contain at least one unit root, the only exception being the earnings in the Netherlands which is apparently trend-stationary. A closer inspection of the results reveals that the ADF and PP tests point to stationarity for other variables than the earnings in the Netherlands. For example, dividends in the UK and in the US are found to be stationary under the PP test allowing for a drift and trend. The ADF and PP tests also suggest that bond yields in the UK and stock index prices in the US are trend-stationary while dividends in Japan may be stationary when only a constant is included. However, these results may not be reliable. First, ADF and PP tests are known to suffer from poor size properties, especially when time series contain large negative MA components (Schwert, 1989). Second, no other unit root test confirms the ADF and PP results. In particular, the NP tests, that were developed by Ng and Perron (2001) to improve the size and power properties of the original PP tests, never reject the null hypothesis of non-stationarity. The unit root tests applied to the first and second differences of the series confirm that the log series (excluding earnings in the Netherlands) exhibit $I(1)$ attributes.[20]

5.1.2. Trace tests for cointegration rank

Prior to the cointegration trace tests, the optimal lag length must be selected. We rely on the SC/HQ/AIC information criteria and look at the statistical significance of the lagged variables in the VAR model. For Germany, France and the Netherlands, the optimal lag length is unambiguously $k^* = 2$ in both models (with earnings and dividends). The optimal lag length for Japan is either $k^* = 2$ or $k^* = 4$ in both specifications (depending on the criteria), while it is $k^* = 2$ for the UK with dividends and $k^* = 5$ or $k^* = 7$ for the UK with earnings. For the US, the optimal lag length is either $k^* = 5$ or $k^* = 2$ for the model with dividends and $k^* = 4$ for the model with the earnings.

Taking into account these optimal lag lengths, we determine the cointegration rank of the VAR system as well as the number and nature of its deterministic components for all countries. Results are given in Tables IV and V. As Model 3 seems to be the most appropriate model given the graphical analysis of the data, we first examine whether it exhibits a cointegration relationship. We then use the so-called Pantula principle to check our results. For Germany, according to Model 3, the VAR with dividends is cointegrated of order 1 as we reject the null of no cointegration vector and do not reject the null of one cointegration vector. The Pantula principle suggests one cointegration vector but selects Model 2 as the most appropriate model. There is no evidence of cointegration in the VAR model with earnings. There is no cointegration for either France or Japan. While this outcome is puzzling for France, it was somewhat

[20] Although the tables are not reported, they are available from the authors upon request.

expected for Japan as its economy has gone through 15 years of bull market followed by 15 years of bear market, with some deflation. The VAR with dividends for the Netherlands clearly exhibits one cointegration vector in Model 3. The Pantula principle confirms the presence of cointegration but points to Model 2 as the most appropriate model. Cointegration in the VAR with earnings is somewhat weaker, but still substantial, as the null of no cointegration is rejected within Model 3 whatever the value of k^*. In the UK, there appears to be more than one cointegration vector in the VAR system with dividends. Assuming Model 3 is correct, we identify three cointegration vectors. The Pantula principle indicates at least two cointegration vectors. In the VAR with earnings, only one cointegration vector is clearly identified and the Pantula principle confirms the selection of Model 3. Finally, the VAR with dividends in the US clearly exhibits one cointegration vector. The Pantula principle also selects Model 3. The analysis of the VAR with earnings yields more conflicting results, although one cointegration vector is found using $k^* = 4$ and Model 3.

5.1.3. Cointegrated VAR estimation and further restrictions

The cointegration results given in Table VI support the view that, for some countries in our dataset, there exists a long-run stable equilibrium between earnings (or dividends), stock prices and bond yields. When the coefficients on the long-run relationship are significantly different from zero, they show the expected signs in all cases. Although β_r is not always significantly different from zero, the bond yield seems to play a significant role in the long-term relationship, at least for some countries and especially for the 1975 - 2000 period. On a monthly basis, the BEYR thus contains more information than the price-earnings (or price-dividends) ratio.

When the adjustment speed coefficients are significantly different from zero, they also show the expected signs in all cases. Their small absolute values indicate a rather slow dynamical adjustment. An impulse response analysis (not reported but available on request) confirms that shocks do not die away quickly and that a given variable needs about 5 years to reach its new long term value. This implies that equity and bond yields might depart from their long-term relationship for an extended period of time before the adjustment process finally bring them back to equilibrium. This is also consistent with the pronounced peaks and troughs of the BEYR (see Figures 1 to 2) and the subsequent stock price adjustments. Note that α_r is almost never significantly different from zero, which implies that the bond yield variable is not affected (at the monthly interval) by the disequilibrium term of the cointegration relationship. A country-by-country analysis reveals some interesting differences. In Germany, the bond yield is not significant in the long-term relationship. This is in stark contrast with the Netherlands, the UK and the US. In these three countries, the bond yield is particularly significant in the VAR with dividends. Additional insight into the cointegrated VAR models is gained by testing two types of restrictions (see Table VII). First, we show that the $(1, -1, -1)$ linear restriction on the cointegration vector is rejected for all countries. As they do not test for cointegration, most studies dealing with the BEYR are therefore wrong in assuming that the variables are cointegrated with 'constrained' weights equal to $(1, -1, -1)$ for the long-term relationship. Secondly, we check whether the p and r variables are weakly exogenous to the system.[21] The dynamics of our cointegrated VAR models is rather strong since the loadings on p and r are jointly significantly different from zero in all countries but Germany.

5.2. Statistical evaluation of the BEYR forecasts

A quick inspection of the results in Tables VIII to XI reveals that it is challenging to deliver relevant out-of-sample forecasts for the BEYR from a statistical point of view. When assessed according to the standard error metrics, the random walk model ranks first or second in each country and in almost all cases. The only exceptions are the MedAE and MedSE in Germany. The Markov switching model based on the forecasted *value* of the BEYR (MS) is the worst performer. Although the cointegration model (COINT) is not a star performer, it ranks among the first five models in a significant number of cases. Interestingly, it performs best for the BEYR specification with dividends in both the US and the UK, as well as for the BEYR specification with earnings in the Netherlands. The percentage of correct predictions in direction changes (DA) shows that most models correctly predict over 50% of next-month directions in every country, excluding the UK. Based on the PT test, the Markov switching model performs well in the US for both specifications of the BEYR. It ranks first and is the only model for which the null hypothesis is rejected at the 10% level of significance. However, the model does not show any consistent market-timing ability as it never reiterates this performance in the other countries. It actually performs badly in the UK. In contrast, the cointegration model is robust in its ability to forecast direction changes in the BEYR. While the null hypothesis

[21] If the adjustment speed coefficient of a variable is not statistically different from zero, the variable is weakly exogenous to the ECM-VAR system. In others words, the variable is not affected by the cointegration vector.

of no market-timing ability is not rejected at the 10% level in 50% of the cases, the COINT model ranks in eight cases out of nine among the first five positions. Moreover, it has significant market-timing ability in the Netherlands.

The Modified Diebold and Mariano (MDM) test shows that the null hypothesis of equal predictive ability (EPA) between the random walk and the competing model is rejected in quite a few cases. The worst results are obtained for the BEYR specification with dividends in the US and for the BEYR specification with earnings in the Netherlands. In these two cases, only one single competing model is as equally accurate as the random walk at the 5% level. In contrast to these results and excluding the Markov switching model, the null hypothesis of EPA is never rejected at the 5% level for the BEYR specification with earnings in the US, the UK and the Netherlands, as well as for the BEYR specification with dividends in Germany. The Markov-switching model is by far the worst performer since the null hypothesis of EPA is rejected in every case at the 5% level. The cointegration model performs better as the null of EPA is rejected in four cases out of nine at the 5% level. Taking into account the results of the sign test, there are some differences in the overall performance of the models. First, the null hypothesis of EPA between the random walk and the competing model is rejected less often at the 5% level than in the MDM test. Secondly, there is always more than one model for which the null is not rejected, even at the 10% level. This shows that the models as a whole seem to perform better than previously suggested by the MDM test. Finally, the cointegration model performs better as the null hypothesis is rejected at the 5% level only in the Netherlands.

The SPA test confirms that the BEYR is a rather difficult financial ratio to forecast. The null hypothesis that the random walk model is not inferior to *any* competing model is never rejected, even at the 10% level. Moreover, the random walk model obtains the highest *P*-value in four cases out of nine. Regarding the MS model based on the forecasted value of the BEYR, the null of SPA is rejected in all cases at the 1% level. We therefore do not investigate further the trading profitability of this model in order to alleviate the potential data snooping problem. For the cointegration model however, the null hypothesis of the SPA test is never rejected at the 5% level. We therefore proceed with the cointegration model and evaluate it from the trading perspective.

Taking all these results into account, we now identify, for each country, the model that gets the best average ranking regarding the accuracy metrics *and* for which the null hypothesis of the SPA, Sign and MDM tests are not rejected at the 5% level. This model (called the SBP model) will be used in the dynamic allocation exercise as a practical way to benchmark the trading performance of the cointegration model. In each country, the SBP model belongs to the ARMA-type family models. In the US and the UK, the SBP models are respectively the ARMA(1,1) and AR(1) models for both specifications of the BEYR. In the Netherlands, the ARMA(1,1)-PGARCH(1,1) and ARMA(3,3)-GARCH(1,1) models are respectively the SBP models for the BEYR with dividends and with earnings. Finally, the SBP model for the BEYR specification with dividends in Germany is the ARMA(1,1) model.

5.3. Trading profitability

The performance of the switching portfolios along with the strategies of buy-and-hold equities and buy-and-hold 10-year bonds are given in Tables XII to XV. Note that we focus on the five countries for which we did not reject the cointegration hypothesis. We also measure the profitability of trading rules based on the equity yield alone in Tables XVI to XIX. For ease of exposition, we summarize all the results in Table XX.

Switching decisions based on the BEYR are more profitable in the US than in any other country. A close look at the trading rules shows that the Markov switching strategy based on the forecasted *probability* of the BEYR (strategy IV) is the best performing strategy in the US. It consistently delivers larger risk-adjusted returns than any of the two buy-and-hold strategies, whatever the specification of the BEYR and even after allowing for transaction costs. This is also the case for strategy III, which is based on the 90th percentile of the historical range of the BEYR. The Sharpe ratios of strategy III are nevertheless lower than those of strategy IV. Excluding strategy IIC, higher Sharpe ratios (after allowing for transaction costs) are obtained in respectively 8 and 10 (out of 14) cases for the BEYR specifications with dividends (BEYR1) and with earnings (BEYR2). Overall, switching decisions based on BEYR2 seem to be slightly more profitable than those based on BEYR1. Interestingly, the cointegration model performs well in both BEYR1 and BEYR2 panels. It always brings higher risk-adjusted returns that those of the buy-and-hold bond portfolio and always beats the SBP and naive models in the BEYR1 panel. Finally, trading rules based on the equity yield are on average less profitable than trading rules based on the BEYR. They nevertheless still rank similarly when they are compared. Strategy IV still ranks first as it is the only strategy that beats the buy-and-hold portfolios in both panels. Strategy III is particularly successful when the earnings yield is used. It however fails to provide higher Sharpe ratios than the buy-and-hold equities portfolio in the dividend yield panel.

In the UK, the Sharpe ratio is higher for the buy-and-hold long-term bond portfolio than for the buy-and-hold equities portfolio.[22] Although most strategies succeed in providing higher risk-adjusted returns than those of the buy-and-hold equities portfolios, they fail to beat the buy-and-hold bond portfolio. The only switching portfolios that are superior to the buy-and-hold equity portfolio for the two specifications of the BEYR, are given by strategy IIB where the switching threshold is given by the 1-year conditional mean of the BEYR. Strategy IIC shows some success but only in the BEYR2 panel. While strategy IV is not a star performer, it never delivers lower risk-adjusted returns than the buy-and-hold equities portfolio. It even beats the buy-and-hold bond portfolio in the BEYR1 panel. Relying on the equity yield does not deliver higher trading profitability. No strategy systematically outperforms the buy-and hold bond portfolio. However, the trading performances of strategies III and IV are again consistent. These two strategies are never inferior to the buy-and-hold equities portfolio and they even outperform the buy-and-hold bond portfolio twice in the BEYR2 panel. While the cointegration model does not systematically beat the naive and SBP models, it does provide the highest Sharpe ratio in the UK (see the top panel of Table XVII).

Regarding the BEYR in the Netherlands, relying on past information is clearly suboptimal. In particular, the naive model systematically generates lower risk-adjusted returns than the two buy-and-hold strategies. Excluding the naive model, switching portfolios generated by strategy IIB outperform the buy-and-hold equities portfolio in both panels. Excluding once again the naive model, strategies IIA and III perform well but only for the BEYR with dividends. Interestingly and for the first time, strategy IV underperforms any of the two buy-and-hold portfolios, whatever the BEYR specification. Although the cointegration model always beats the naive and SBP models in the top panel, it delivers less consistent results than the SBP model. While strategies based on the equity yield are on average less profitable, they generate the best results. Strategy I, and the cointegration model in particular, provides the two highest Sharpe ratios in the Netherlands (see Table XVIII).

[22] Surprisingly, Brooks and Persand (2001) set the Sharpe ratio of the buy-and-hold long-term bond portfolio to zero by using the return on long-term bonds as the risk-free proxy. While they do this ‘for comparability with the remainder of the analysis’, it is far from being inconsequential. In countries like the UK and Germany (which are included in their study), the Sharpe ratio of the buy-and-hold 10-year bond portfolio is larger than the Sharpe ratio of the buy-and-hold equities portfolio over the 1988-2004 time period. Therefore, while the risk-adjusted returns of some switching portfolios may look superior to those of the buy-and-hold equities portfolio, they may actually be inferior to those of the buy-and-hold 10-year bond portfolio.

In Germany, strategy IV is the only strategy that succeeds in beating the buy-and-hold bond portfolio. Strategy III ranks second as it is the only alternative that systematically outperforms the buy-and-hold equities portfolio. As to the dividend yield, it clearly brings inferior trading performance. The buy-and-hold bond portfolio is never outperformed while the buy-and-hold equities portfolio is only beaten by strategy IIA.

6. Conclusion

While a large number of financial ratios somewhat help predict long-term stock returns, researchers have been less successful in identifying financial variables that help time the market on a short-term basis. Moreover, the evidence for the predictability of stock returns comes primarily from in-sample predictive regression models. In this paper, we suggest the use of the Bond-Equity Yield Ratio (BEYR) to dynamically allocate capital between equities and bonds on a short-term basis. In a first step, we model the BEYR constituents (earnings or dividends, stock prices, long-term government bond yields) in a multivariate econometric framework based on cointegration techniques. Secondly, we model the BEYR ratio in an univariate framework using Markov switching regime and ARMA-GARCH type models. All these approaches deliver out-of-sample BEYR forecasts upon which trading rules are based.

As far as the cointegration analysis is concerned, we do find a valid and meaningful long-term cointegrating relationship between stock index prices, earnings (or dividends) and bond yields for the US, the UK, the Netherlands and Germany. The coefficients on the long-run relationship always show the expected signs when they are significantly different from zero. Overall, the results suggest that the BEYR does contain more information than the simple equity yield on a monthly basis. From a statistical perspective, we show that our sophisticated BEYR models have a hard time outperforming the random walk when the out-of-sample forecasts are assessed. However, the cointegration model delivers stable results throughout the sample. In this respect, it performs well in comparison to the other forecasting models.

Finally, we assess the forecasting power of the models from an economic perspective, i.e. by implementing trading rules decisions that rely on a comparison of the BEYR forecasts with some appropriately defined thresholds. For most countries, the BEYR delivers higher risk-adjusted returns than the equity yield on a short-term basis. The US is the country where the trading profitability is the highest. Although the BEYR with earnings in the US delivers higher risk-adjusted returns than the BEYR with dividends, the former does not systematically outperform the latter when the whole sample of countries is looked at. The Markov switching strategy based on the forecasted *probability* of the BEYR is clearly the best performing strategy across the sample. A trading strategy based on the distribution percentiles also shows some consistency in its ability to outperform the buy-and-hold strategies. Finally, the cointegration model seems to be rather successful as it beats the naive and SBP models in most cases.

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Table I
Summary Statistics for the Bond-Equity Yield Ratio.

BEYR with dividends	GE	FR	JP	NL	UK	US
Mean	2.86	2.43	4.58	1.83	2.15	2.75
Median	2.88	2.29	4.12	1.76	2.13	2.54
Maximum	5.36	4.44	13.83	3.27	3.19	5.96
Minimum	1.29	1.06	0.64	1.01	1.03	1.52
Std Dev	0.74	0.60	2.53	0.45	0.33	0.88
Skewness	0.37	0.58	1.25	0.85	-0.02	1.51
Kurtosis	2.97	3.01	4.60	3.53	3.91	5.25
Jarque-Bera	8.19**	20.24***	132.92***	48.10***	12.50***	214.22***
Ljung box Q^*	2559.87***	2392.22***	3532.43***	2661.96***	1456.32***	3397.67***
ARCH(7)	358.23***	185.63***	649.17***	376.30***	120.55***	771.47***

BEYR with earnings	GE	FR	JP	NL	UK	US
Mean	0.95	1.09	1.67	0.87	1.23	1.19
Median	0.93	1.02	1.68	0.84	1.25	1.18
Maximum	1.62	2.15	3.78	1.75	1.77	1.96
Minimum	0.38	0.41	0.26	0.42	0.52	0.67
Std Dev	0.28	0.34	0.70	0.25	0.22	0.25
Skewness	0.36	0.43	0.37	0.61	-0.56	0.21
Kurtosis	2.24	2.97	3.21	3.19	3.63	3.35
Jarque-Bera	16.51***	11.03***	8.93**	23.21***	24.60***	4.54
Ljung box Q^*	2297.14***	2508.83***	3105.52***	2689.82***	1462.12***	2204.65***
ARCH(7)	224.54***	277.84***	306.37***	274.28***	172.94***	287.63***

ARCH(7) denotes Engle's LM test for autoregressive conditional heteroscedasticity of up to seventh order. The test statistic follows an $F(7, 372)$ distribution under the null of no ARCH effect. GE, FR, JP, NL, UK, US respectively stand for Germany, France, Japan, Netherlands, United Kingdom and United States. */**/*** rejects the null hypothesis at the 10/5/1% levels.

Table II

Unit Root Tests (I): Logs of Dividends, Earnings, Stock Index Prices and Long-Term Bond Yields.

		ADF			PP			DFGLS		ERSPO	
Country	Data	-.-	C.-	C.T	-.-	C.-	C.T	C.-	C.T	C.-	C.T
GE	D	1.51	0.25	-1.99	2.77	0.26	-1.99	0.77	-1.35	147.63	24.35
	E	1.65	-1.26	-2.48	1.56	-1.29	-2.70	1.25	-2.46	114.56	7.47
	S	1.23	-0.89	-1.79	1.15	-0.92	-2.10	0.26	-1.47	65.99	18.24
	B	-1.06	-1.44	-2.32	-1.05	-1.18	-2.27	-0.59	-2.29	9.34	8.18
FR	D	1.70	-1.62	-2.76	4.41	-1.44	-2.40	1.08	-1.79	601.84	8.87
	E	2.08	-1.43	-2.44	2.08	-1.43	-2.49	1.45	-1.95	158.72	12.17
	S	1.49	-0.54	-2.13	1.73	-0.67	-2.50	0.74	-1.69	87.27	19.39
	B	-1.11	-0.17	-1.93	-0.73	-0.51	-2.49	-0.54	-0.87	14.74	39.77
JP	D	1.34	-2.61*	-1.33	1.42	-2.66*	-1.25	0.49	-0.49	142.03	46.24
	E	0.39	-1.96	-2.06	0.67	-1.97	-1.64	-0.40	-1.77	23.35	13.33
	S	0.85	-1.36	-0.20	0.77	-1.37	-0.37	-0.10	-0.60	68.13	36.62
	B	-1.29	0.38	-2.10	-1.17	0.44	-2.39	0.93	-1.11	31.15	22.61
NL	D	2.17	-0.02	-2.70	5.10	-0.02	-2.70	1.06	-2.00	601.89	12.24
	E	1.78	-1.17	-3.23*	1.67	-1.20	-3.73**	1.10	-2.98**	95.57	5.49**
	S	0.93	-0.46	-2.39	1.77	-0.43	-2.61	-0.37	-1.23	99.78	36.51
	B	-0.78	-0.90	-2.80	-0.82	-0.75	-2.57	-0.90	-1.70	7.40	14.63
UK	D	1.46	-2.52	0.98	5.08	-3.69***	0.98	0.61	-0.58	830.76	146.00
	E	2.36	-1.63	-1.50	2.48	-2.10	-2.70	1.65	-1.24	356.06	33.87
	S	1.77	-1.02	-1.58	1.86	-0.95	-1.53	0.77	-1.70	120.12	13.29
	B	-1.06	-0.05	-3.41*	-1.01	0.24	-3.47*	-0.05	-1.07	17.24	30.77
US	D	1.96	-1.61	-1.65	5.02	-3.02**	-0.31	1.48	-1.35	970.92	29.62
	E	2.36	-1.45	-2.84	3.26	-1.51	-2.50	1.65	-2.24	252.71	11.57
	S	2.54	0.13	-3.16*	2.55	0.13	-3.17*	1.65	-1.09	147.34	43.42
	B	-0.64	-0.90	-2.33	-0.63	-0.76	-2.20	-1.05	-1.14	7.81	25.65

Outcomes of the following tests: Augmented Dickey-Fuller (ADF), Philipps-Perron (PP), Dickey-Fuller GLS de-trended (DFGLS) and Elliott-Rothenberg-Stock Point-Optimal (ERSPO). Critical Values for the ERSPO test can be found Elliott and al. (1996, Table 1) while those for the ADF, PP and DFGLS tests are from MacKinnon (1996). The information criterion used in these tests is the MAIC as defined by Ng and Perron (2001). The spectral estimation methods used in the PP and ERSPO tests are respectively the Bartlett kernel and AR spectral OLS methods. C and T respectively indicate that a constant and a trend have been included in the test. D, E, S and B respectively mean dividends, earnings, stock index prices and bond yields. GE, FR, JP, NL, UK, US respectively stand for Germany, France, Japan, Netherlands, United Kingdom and United States. */**/*** rejects the null hypothesis at the 10/5/1% levels.

Table III
Unit Root Tests (II): Logs of Dividends, Earnings, Stock Index Prices and Long-Term Bond Yields.

		NP								KPSS	
		C,-				C,T				C,-	C,T
Country	Data	MZa	MZt	MSB	MPT	MZa	MZt	MSB	MPT		
GE	D	1.24	1.08	0.87	56.68	-3.86	-1.35	0.35	23.11	2.16***	0.34***
	E	0.99	1.01	1.03	73.18	-9.29	-2.15	0.23	9.81	2.01***	0.10
	S	0.27	0.27	1.01	60.83	-5.02	-1.45	0.29	17.59	2.21***	0.11
	B	-2.19	-0.70	0.32	8.86	-11.75	-2.36	0.20	8.13	1.27***	0.15**
FR	D	1.11	1.66	1.49	150.04	-10.86	-2.22	0.20	8.94	2.31***	0.22***
	E	1.01	1.47	1.45	139.75	-7.88	-1.93	0.24	11.72	2.21***	0.15**
	S	0.70	0.76	1.10	77.64	-6.09	-1.69	0.28	14.94	2.25***	0.12*
	B	-1.15	-0.51	0.45	13.60	-2.12	-0.89	0.42	35.79	1.59***	0.38***
JP	D	0.35	0.51	1.47	122.73	-1.10	-0.48	0.44	43.17	1.91***	0.54***
	E	-0.82	-0.49	0.60	20.59	-7.29	-1.85	0.25	12.63	1.21***	0.43***
	S	-0.08	-0.09	1.07	61.89	-1.51	-0.60	0.40	36.53	1.80***	0.46***
	B	1.95	1.05	0.54	29.30	-3.73	-1.15	0.31	21.55	1.97***	0.36***
NL	D	1.36	1.97	1.45	149.56	-7.81	-1.98	0.25	11.67	2.32***	0.18**
	E	1.00	1.11	1.11	84.93	-17.16*	-2.91**	0.17**	5.40*	2.20***	0.12*
	S	-0.13	-0.08	0.65	26.94	-3.21	-1.24	0.38	27.65	2.23***	0.17**
	B	-3.23	-0.95	0.29	7.31	-6.76	-1.72	0.25	13.60	1.52***	0.16**
UK	D	0.66	0.77	1.16	85.63	-3.28	-0.99	0.30	22.42	2.28***	0.53***
	E	0.93	1.75	1.87	225.04	-4.08	-1.24	0.30	20.39	2.30***	0.32***
	S	0.62	0.80	1.29	103.34	-7.61	-1.77	0.23	12.42	2.29***	0.32***
	B	-0.15	-0.07	0.46	16.90	-3.01	-1.10	0.37	27.24	1.98***	0.30***
US	D	0.89	1.26	1.41	129.43	-4.21	-1.20	0.29	19.42	2.29***	0.45***
	E	1.09	1.69	1.54	160.38	-11.30	-2.31	0.20	8.45	2.25***	0.16**
	S	1.18	1.66	1.41	136.70	-2.34	-1.08	0.46	39.00	2.26***	0.36***
	B	-3.05	-1.06	0.35	7.77	-3.53	-1.17	0.33	23.22	1.27***	0.39***

Outcomes of the following tests: the Ng and Perron (NP) tests and the Kwiatkowski, Phillips, Schmidt, and Shin (KPSS) test. The MZa, MZt, MSB and MPT tests are based upon GLS detrended data and are respectively modified forms of: Phillips and Perron Z_a and Z_t statistics, Bhargava (1986) R_1 statistic and the ERSPO statistic. Critical Values of the NP and KPSS tests can respectively be found in Ng and Perron (2001, Table 1) and Kwiatkowski and al. (1992, Table 1). The KPSS test has a null hypothesis of stationarity. The spectral estimation methods used in the NP and KPSS are respectively the AR GLS-detrended and Bartlett kernel methods. C and T respectively indicate that a constant and a trend have been included in the test. D, E, S and B respectively mean dividends, earnings, stock index prices and bond yields. GE, FR, JP, NL, UK, US respectively stand for Germany, France, Japan, Netherlands, United Kingdom and United States. */**/*** rejects the null hypothesis at the 10/5/1% levels.

Table IV

Tests for the Cointegration Rank and the Deterministic Components: The VAR with Dividends.

Country	$H_0: c = i$	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4
			$k=2$			$k=1$			$k=3$	
GE	$i=0$	42.09**	33.93**	42.48*	57.91***	43.88***	53.58***	38.71**	30.79**	39.94*
	$i=1$	13.05	9.35	17.23	12.14	6.41	13.82	11.20	7.67	16.09
	$i=2$	3.39	0.15	5.81	4.74	0.00	3.64	3.37	0.10	5.34
			$k=2$			$k=1$			$k=3$	
FR	$i=0$	47.12***	20.53	37.60	55.16***	24.51	46.83**	42.46***	19.43	37.33
	$i=1$	12.76	3.69	16.11	14.74	3.35	16.79	12.53	3.59	15.27
	$i=2$	3.59	0.09	2.75	3.31	0.00	2.26	3.46	0.11	2.73
			$k=2$			$k=4$			$k=1$	
JP	$i=0$	28.87	22.58	41.40*	33.21*	24.93	40.59*	28.55	23.29	41.81*
	$i=1$	9.71	5.43	21.18	12.09	5.51	18.46	9.35	5.09	19.22
	$i=2$	1.77	1.37	4.02	2.11	0.38	4.45	2.08	1.97	3.11
			$k=2$			$k=1$			$k=3$	
NL	$i=0$	64.84***	37.20***	52.44***	76.61***	44.31***	64.51***	62.69***	37.76***	53.26***
	$i=1$	16.00	9.81	22.61	17.33	7.69	24.91	15.05	10.24	23.62*
	$i=2$	5.01	0.07	9.54	3.67	0.01	7.54	3.36	0.21	9.98
			$k=2$			$k=1$			$k=3$	
UK	$i=0$	112.42***	52.97***	74.60***	125.69***	50.82***	66.26***	93.94***	47.98***	65.45***
	$i=1$	27.475***	25.88***	43.80***	27.32***	25.94***	40.86***	24.40**	23.52***	39.58***
	$i=2$	6.85	6.84***	18.82***	8.31*	7.85***	16.71***	5.53	5.30**	17.86***
			$k=5$			$k=2$			$k=3$	
US	$i=0$	40.33**	27.64*	42.22**	53.46***	30.46**	39.84*	50.98***	29.15*	38.74
	$i=1$	19.88*	12.82	22.70	18.92*	12.21	20.88	19.19*	13.20	23.19
	$i=2$	7.04	0.40	9.38	7.85	1.21	9.74	6.77	0.80	8.97

Outcomes for the trace test. Model 2, Model 3 and Model 4 respectively include a restricted constant, an unrestricted constant and both a restricted trend and an unrestricted constant. GE, FR, JP, NL, UK, US respectively stand for Germany, France, Japan, Netherlands, United Kingdom and United States. */**/*** rejects the null hypothesis at the 10/5/1% levels.

Table V
Tests for the Cointegration Rank and the Deterministic Components: The VAR with Earnings.

Country	$H_0 : c = i$	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4	Model 2	Model 3	Model 4
			$k=2$			$k=1$			$k=3$	
GE	$i=0$	32.97	27.4	34.24	31.03	23.78	31.90	29.73	24.43	31.56
	$i=1$	10.21	6.42	12.04	8.47	3.56	9.82	9.62	5.93	12.18
	$i=2$	4.01	0.25	5.18	2.89	0.06	2.89	3.85	0.16	4.99
			$k=2$			$k=1$			$k=3$	
FR	$i=0$	31.48	20.77	31.88	32.75*	21.40	38.64	29.07	19.01	29.31
	$i=1$	9.34	3.85	11.41	9.54	4.02	12.53	10.32	3.89	11.15
	$i=2$	3.79	0.05	2.80	3.66	0.00	2.40	3.81	0.04	2.70
			$k=2$			$k=4$			$k=1$	
JP	$i=0$	23.20	19.85	41.60*	22.54	18.07	34.97	24.11	20.02	36.49
	$i=1$	3.95	2.39	18.17	6.13	2.77	13.04	5.00	1.97	12.50
	$i=2$	1.65	0.34	1.72	2.46	0.02	2.30	1.62	0.22	1.52
			$k=2$			$k=5$			$k=3$	
NL	$i=0$	37.67**	29.82**	35.64	40.48***	33.51**	36.61	43.78***	34.84**	40.87*
	$i=1$	15.66	9.13	14.40	17.51	11.51	14.32	14.47	5.85	11.02
	$i=2$	5.57	0.25	5.36	3.03	1.00	3.27	4.44	0.15	4.41
			$k=7$			$k=5$			$k=2$	
UK	$i=0$	68.41***	56.69***	70.53***	55.46***	43.77***	57.07***	55.96***	31.54**	45.65**
	$i=1$	21.81**	11.63	23.74	21.22**	11.10	24.40*	20.51**	10.84	17.21
	$i=2$	5.65	5.26**	5.45	6.07	4.74**	4.76	5.84	4.49**	5.46
			$k=4$			$k=3$			$k=5$	
US	$i=0$	47.42***	30.51**	34.63	58.20***	25.71	28.36	45.16***	30.28**	35.22
	$i=1$	25.94***	10.86	14.66	23.60**	8.82	10.90	25.07***	10.44	14.31
	$i=2$	9.39**	0.25	3.56	8.46*	0.36	1.91	9.20**	0.32	3.59

Outcomes for the trace test. Model 2, Model 3 and Model 4 respectively include a restricted constant, an unrestricted constant and both a restricted trend and an unrestricted constant. GE, FR, JP, NL, UK, US respectively stand for Germany, France, Japan, Netherlands, United Kingdom and United States. */**/*** rejects the null hypothesis at the 10/5/1% levels.

Table VI
Cointegrated VAR Analysis.

A. Dividends, Stock Index Prices and Bond Yields

Country	Time period	Lags	Model	Cointegration vector β'	α_d	α_p	α_r
GE	73:01 - 04:01	2	3	$(1^{***}$ -0.57^{***} $0.14)$	-0.03^{***}	-0.00	-0.02
	75:01 - 00:01	2	3	$(1^{***}$ -0.60^{***} $0.04)$	-0.04^{***}	0.03	-0.02
NL	73:01 - 04:01	2	3	$(1^{***}$ -0.72^{***} $-0.39^{*})$	-0.04^{***}	0.02	-0.01
	75:01 - 00:01	2	3	$(1^{***}$ -0.71^{***} $-0.56^{***})$	-0.04^{***}	0.09^{***}	
UK	73:01 - 04:01	2	3	$(1^{*}$ -0.95^{*} $-0.90^{**})$	-0.02^{**}	0.03	-0.00
	75:01 - 00:01	2	3	$(1^{***}$ -1.04^{***} $-0.91^{***})$	-0.03^{**}	0.20^{***}	-0.00
US	73:01 - 04:01	2	3	$(1^{***}$ -0.76^{***} $-0.87^{***})$	-0.00^{**}	0.05^{**}	0.02
	75:01 - 00:01	2	3	$(1^{**}$ -0.51^{**} $-0.40^{*})$	-0.00	0.04^{**}	-0.01

B. Earnings, Stock Index Prices and Bond Yields

Country	Time period	Lags	Model	Cointegration vector β'	α_e	α_p	α_r
NL	73:01 - 04:01	2	3	$(1^{***}$ -0.64^{***} $-0.35)$	-0.05^{***}	0.02^{*}	-0.02
	75:01 - 00:01	2	3	$(1^{***}$ -0.72^{***} $-1.00^{***})$	-0.06^{***}	0.05^{***}	0.00
UK	73:01 - 04:01	7	3	$(1^{***}$ -0.78^{***} $-0.19)$	-0.05^{***}	0.07^{***}	-0.00
	75:01 - 00:01	7	3	$(1^{***}$ -0.89^{***} $-0.60^{***})$	-0.06^{***}	0.13^{***}	0.00
US	73:01 - 04:01	4	3	$(1^{***}$ -0.70^{**} $-0.24)$	-0.02^{***}	0.05^{***}	-0.01
	75:01 - 00:01	4	3	$(1^{***}$ -0.76^{***} $-0.69^{***})$	-0.01	0.06^{**}	0.03

The variables included in the ECM-VAR specification are the log dividend index (d), the log earnings index (e), the log stock index (p) and the log government bond yield (r). 'Lags' gives the number of lags included in the ECM-VAR specification. 'Model' indicates the number and nature of the deterministic components included the ECM-VAR system. Model 2, Model 3 and Model 4 respectively includes a restricted constant, an unrestricted constant and both a restricted trend and an unrestricted constant. Using the Johansen methodology, the cointegration vector β gives the coefficient of each variable in the long-run relationship with the first weight on d normalized at 1. If a fourth element is included in the vector β, this refers to a restricted constant (Model 2) or trend (Model 4). The next three columns give the coefficients of adjustment speed for each variable. */**/*** respectively indicates that the coefficient is significantly different from zero at the 10/5/1% level. It is based on the P-value of the $\chi^2(1)$ LR test for binding restriction. GE, NL, UK and US respectively stand for Germany, Netherlands, United Kingdom and United States.

Table VII
Restriction Tests on the Cointegrated VAR Model.

A. Dividends, Stock Index Prices and Bond Yields

Country	Time period	Lags	Model	β'=(1, -1, -1)	$\alpha_p = \alpha_r$=0
GE	73:01 - 04:01	2	3	10.82^{***}	2.27
	75:01 - 00:01	2	3	9.57^{***}	1.94
NL	73:01 - 04:01	2	3	12.12^{***}	2.20
	75:01 - 00:01	2	3	15.64^{***}	9.36^{***}
UK	73:01 - 04:01	2	3	0.48	1.14
	75:01 - 00:01	2	3	12.21^{***}	29.77^{***}
US	73:01 - 04:01	2	3	6.71^{**}	11.00^{***}
	75:01 - 00:01	2	3	10.42^{***}	7.43^{**}

B. Earnings, Stock Index Prices and Bond Yields

Country	Time period	Lags	Model	β'=(1, -1, -1)	$\alpha_p = \alpha_r$=0
NL	73:01 - 04:01	2	3	10.68^{***}	5.27^{*}
	75:01 - 00:01	2	3	14.39^{***}	10.47^{***}
UK	73:01 - 04:01	7	3	20.08^{***}	9.82^{***}
	75:01 - 00:01	7	3	7.50^{**}	24.98^{***}
US	73:01 - 03:01	4	3	7.59^{**}	9.96^{***}
	75:01 - 00:01	4	3	8.61^{**}	7.94^{**}

Outcomes of the LR tests for binding restriction. The statistic follows a $\chi^2(m)$ distribution, with m being the number of constraints. The variables included in the ECM-VAR specification are the log dividend index (d), the log earnings index (e), the log stock index (p) and the log bond yield (r). 'Lags' gives the number of lags included in the ECM-VAR specification. 'Model' indicates the number and nature of the deterministic components included the ECM-VAR system. Model 2 and Model 3 respectively includes a restricted constant and an unrestricted constant. If a fourth element is included in the vector β, this refers to a restricted constant (Model 2). GE, NL, UK and US respectively stand for Germany, Netherlands, United Kingdom and United States. */**/*** respectively indicates that the restriction is rejected at the 10/5/1% levels.

Table VIII

The BEYR in the United States: Statistical evaluation of out-of-sample 1-step ahead forecasts using a rolling window.

Model	MSE	RMSE	MedSE	MAE	MedAE	DA	PT	MDM	Sign	SPA
BEYR with dividends										
COINT(3,2)	0.334(4)	5.777(4)	0.112(2)	4.403(2)	3.345(2)	53.93	13.95(3)	3.25(3)	19.32(1)	14.61(3)
MS	2.439	15.618	0.562	11.423	7.500	55.50	6.62(1)	0.33	0.00	0.00
RW	0.316(1)	5.623(1)	0.107(1)	4.309(1)	3.269(1)	-	-	-	-	63.11(1)
AR(1)	0.331(2)	5.755(2)	0.119(5)	4.451(3)	3.453	52.88	21.39(4)	3.96(2)	12.41(3)	5.02
ARMA(1,1)	0.331(2)	5.756(3)	0.123	4.453(4)	3.502	53.93	13.75(2)	7.60(1)	15.61(2)	20.55(2)
ARMA(1,0)-GARCH(1,1)	0.336(5)	5.794(5)	0.120	4.506	3.457	52.88	21.39(4)	1.75(4)	5.62	8.84(4)
ARMA(1,0)-EGARCH(1,1)	0.338	5.810	0.119(5)	4.479(5)	3.450(5)	52.88	21.39(4)	0.67	1.52	3.98
ARMA(1,0)-TGARCH(1,1)	0.337	5.800	0.118(3)	4.498	3.428(3)	52.36	25.92	0.80	12.41(3)	4.89
ARMA(1,0)-PGARCH(1,1)	0.339	5.819	0.120	4.518	3.462	52.36	25.92	0.55	9.70(5)	3.03
ARMA(1,1)-CGARCH(1,0)	0.341	5.842	0.118(3)	4.543	3.431(4)	51.31	35.91	1.06(5)	7.45	5.91(5)
BEYR with earnings										
COINT(3,4)	0.364	6.032	0.135(4)	4.540	3.671(4)	50.79	41.54	19.30	76.48(1)	25.27
MS	1.777	13.330	0.472	9.471	6.869	54.97	8.61(1)	1.33	0.00	0.12
RW	0.346(2)	5.885(2)	0.127(1)	4.507(2)	3.562(1)	-	-	-	-	74.31(4)
AR(1)	0.350(4)	5.913(4)	0.134(3)	4.508(3)	3.656(3)	52.36	25.78(3)	37.30(3)	50.00(2)	78.83(3)
ARMA(1,1)	0.345(1)	5.874(1)	0.128(2)	4.500(1)	3.580(2)	53.40	17.37(2)	53.72(1)	44.26(3)	81.66(2)
ARMA(1,0)-GARCH(1,1)	0.351(5)	5.925(5)	0.144	4.522(5)	3.793	52.36	25.78(3)	34.78(5)	44.26(3)	50.15(5)
ARMA(1,0)-EGARCH(1,1)	0.353	5.942	0.143	4.543	3.781	51.83	30.74	28.05	28.19	33.55
ARMA(1,0)-TGARCH(1,1)	0.357	5.975	0.140	4.580	3.743	50.79	41.36	21.25	44.26(3)	20.12
ARMA(1,0)-PGARCH(1,1)	0.347(3)	5.895(3)	0.139(5)	4.519(4)	3.729(5)	52.36	25.78(3)	45.96(2)	38.64	83.60(1)
ARMA(2,0)-CGARCH(1,0)	0.352	5.932	0.140	4.557	3.745	50.79	41.71	36.95(4)	38.64	41.61

The standard prediction evaluation metrics have been multiplied by 100. The DA is reported in percentage terms. The *P*-values of the PT, MDM, sign and SPA tests have been multiplied by 100 and are all based on one-sided tests. Rankings are in brackets.

Table IX

The BEYR in the UK: Statistical evaluation of out-of-sample 1-step ahead forecasts using a rolling window.

Model	MSE	RMSE	MedSE	MAE	MedAE	DA	PT	MDM	Sign	SPA
BEYR with dividends										
COINT(3,2)	0.255(5)	5.051(5)	0.078(4)	3.656(3)	2.787(4)	49.74	54.66(2)	4.60	33.25(1)	16.32
MS	1.85	13.61	0.21	8.62	4.63	46.07	92.99	2.59	0.00	0.24
RW	0.232(1)	4.817(1)	0.055(1)	3.547(1)	2.350(1)	-	-	-	-	58.65(1)
AR(1)	0.249(2)	4.990(2)	0.061(2)	3.608(2)	2.471(2)	47.64	75.29(3)	13.44(1)	33.25(1)	36.13(2)
ARMA(1,1)	0.252(3)	5.022(3)	0.074(3)	3.693(5)	2.716(3)	49.73	54.11(1)	8.09(4)	23.52(3)	26.25(3)
ARMA(1,0)-GARCH(1,1)	0.268	5.176	0.084	3.783	2.900	47.12	79.84	5.16	12.41	10.64
ARMA(1,0)-EGARCH(1,1)	0.254(4)	5.045(4)	0.078(4)	3.688(4)	2.787(4)	47.64	75.29(3)	10.06(2)	23.52(3)	20.86(4)
ARMA(1,0)-TGARCH(1,1)	0.260	5.096	0.084	3.740	2.898	47.64	75.74(5)	8.72(3)	15.62	20.23(5)
ARMA(1,0)-PGARCH(1,1)	0.269	5.183	0.085	3.770	2.913	47.12	79.84	4.95	23.52(3)	13.19
ARMA(1,0)-CGARCH(1,0)	0.266	5.161	0.079	3.759	2.807	47.12	79.84	5.19(5)	12.41	8.05
BEYR with earnings										
COINT(3,5)	0.270	5.199	0.082	3.863	2.871	53.40	16.65(1)	9.44	33.25(1)	23.89
MS	1.602	12.659	0.433	9.110	6.582	44.50	95.65	0.94	0.00	0.06
RW	0.254(1)	5.036(1)	0.071(1)	3.745(1)	2.667(1)	-	-	-	-	87.79(1)
AR(1)	0.265(3)	5.145(3)	0.073(2)	3.783(2)	2.698(2)	50.79	43.89	13.77(4)	19.32(3)	39.11(4)
ARMA(8,8)	0.284	5.331	0.085	3.994	2.915	53.40	17.16(2)	36.77(1)	23.52(2)	10.32
ARMA(1,0)-GARCH(1,1)	0.269(4)	5.188(5)	0.077(5)	3.842(4)	2.773(5)	51.31	38.61(4)	10.76	12.41(4)	44.58(2)
ARMA(1,0)-EGARCH(1,1)	0.272	5.212	0.077(5)	3.859	2.773(5)	52.36	26.81(3)	17.30(3)	5.62	21.52
ARMA(1,0)-TGARCH(1,1)	0.271	5.203	0.089	3.889	2.987	49.21	62.28	10.50	4.16	22.25
ARMA(1,0)-PGARCH(1,1)	0.264(2)	5.142(2)	0.074(3)	3.807(3)	2.723(3)	50.26	50.85	18.57(2)	12.41(4)	37.61(5)
ARMA(1,0)-CGARCH(1,0)	0.269(4)	5.187(4)	0.075(4)	3.843(5)	2.741(4)	51.31	38.61(4)	10.81(5)	5.62	43.01(3)

The standard prediction evaluation metrics have been multiplied by 100. The DA is reported in percentage terms. The *P*-values of the PT, MDM, sign and SPA tests have been multiplied by 100 and are all based on one-sided tests. Rankings are in brackets.

Table X
The BEYR in the Netherlands: Statistical evaluation of out-of-sample 1-step ahead forecasts using a rolling window.

Model	MSE	RMSE	MedSE	MAE	MedAE	DA	PT	MDM	Sign	SPA
BEYR with dividends										
COINT(3,2)	0.390	6.244	0.088	4.270	2.974	55.50	6.40(5)	14.39	3.03	31.14
MS	2.893	17.010	0.701	11.796	8.373	54.45	11.93	2.01	0.00	0.28
RW	0.357(2)	5.973(2)	0.071(1)	4.072(1)	2.673(1)	-	-	-	-	69.69(4)
AR(2)	0.372	6.101	0.085(4)	4.194	2.922(5)	56.02	4.88(3)	26.30(4)	5.62	34.70(5)
ARMA(4,6)	0.410	6.407	0.100	4.343	3.164	53.93	14.94	15.15	9.70(5)	19.06
ARMA(1,1)-GARCH(1,1)	0.360(4)	6.001(4)	0.099	4.155(4)	3.144	56.02	4.95(4)	41.28(3)	12.41(4)	76.37(2)
ARMA(1,1)-EGARCH(1,1)	0.369(5)	6.072(5)	0.081(2)	4.151(3)	2.846(2)	55.50	6.58	23.58(5)	44.26(1)	28.88
ARMA(2,0)-TGARCH(1,1)	0.359(3)	5.990(3)	0.084(3)	4.144(2)	2.903(3)	56.54	3.61(1)	44.91(2)	9.70(5)	74.79(3)
ARMA(1,1)-PGARCH(1,1)	0.356(1)	5.965(1)	0.085(4)	4.160(5)	2.917(4)	55.50	6.49	52.79(1)	33.25(2)	84.32(1)
ARMA(2,0)-CGARCH(1,0)	0.478	6.912	0.097	4.538	3.109	56.54	3.61(1)	6.88	33.25(2)	9.69
BEYR with earnings										
COINT(3,2)	0.425(3)	6.516(3)	0.115(2)	4.741(4)	3.385(2)	56.02	4.83(3)	2.03(5)	4.16	7.32(4)
MS	3.055	17.478	1.331	13.713	11.538	50.79	37.56	0.33	0.00	0.02
RW	0.395(1)	6.285(1)	0.099(1)	4.526(1)	3.147(1)	-	-	-	-	80.00(1)
AR(1)	0.421(2)	6.489(2)	0.126(3)	4.706(2)	3.552(3)	55.50	6.44(5)	0.97	12.41(3)	4.92
ARMA(5,3)	0.459	6.774	0.162	5.038	4.022	53.40	17.36	2.29(3)	7.45(4)	6.94(5)
ARMA(3,3)-GARCH(1,1)	0.433	6.581	0.128(4)	4.722(3)	3.574(4)	53.93	13.50	6.46(1)	7.44(4)	12.77(2)
ARMA(8,8)-EGARCH(1,0)	0.479	6.921	0.156	5.148	3.952	53.40	17.47	0.32	5.62	0.79
ARMA(2,2)-TGARCH(1,1)	0.429(5)	6.548(5)	0.136(5)	4.745(5)	3.690	55.50	6.24(4)	2.84(2)	19.32(1)	10.13(3)
ARMA(3,0)-PGARCH(1,0)	0.426(4)	6.529(4)	0.136(5)	4.770	3.682(5)	57.07	2.50(2)	1.26	0.00	5.09
ARMA(8,6)-CGARCH(1,0)	0.481	6.935	0.144	5.044	3.792	58.64	0.82(1)	2.25(4)	15.62(2)	4.79

The standard prediction evaluation metrics have been multiplied by 100. The DA is reported in percentage terms. The *P*-values of the PT, MDM, sign and SPA tests have been multiplied by 100 and are all based on one-sided tests. Rankings are in brackets.

Table XI
The BEYR in Germany: Statistical evaluation of out-of-sample 1-step ahead forecasts using a rolling window.

Model	MSE	RMSE	MedSE	MAE	MedAE	DA	PT	MDM	Sign	SPA
BEYR with dividends										
COINT(3,2)	0.530(5)	7.278(5)	0.181	5.291(5)	4.258	53.93	14.48(5)	34.22(4)	50.00(2)	53.40(5)
MS	4.366	20.896	1.081	14.973	10.398	52.88	19.20	0.72	0.00	0.01
RW	0.521(1)	7.215(1)	0.149(5)	5.252(1)	3.857(5)	-	-	-	-	89.31(2)
AR(2)	0.526(3)	7.253(3)	0.153	5.282(3)	3.910	52.36	26.15	39.10(2)	50.00(2)	86.52(3)
ARMA(1,1)	0.526(3)	7.253(3)	0.151	5.274(2)	3.885	52.88	21.81	38.23(3)	66.75(1)	91.50(1)
ARMA(1,0)-GARCH(1,1)	0.534	7.306	0.140(2)	5.288(4)	3.748(3)	54.45	11.34(3)	32.94(5)	15.62	47.39
ARMA(1,0)-EGARCH(1,1)	0.543	7.372	0.141(4)	5.324	3.750(4)	54.97	8.72(1)	25.42	28.19(4)	25.78
ARMA(1,0)-TGARCH(1,1)	0.542	7.361	0.134(1)	5.323	3.661(1)	54.45	11.34(3)	24.80	12.41	34.37
ARMA(1,0)-PGARCH(1,1)	0.544	7.375	0.140(2)	5.313	3.746(2)	54.97	8.87(2)	24.16	9.70	27.92
ARMA(1,3)-CGARCH(1,0)	0.521(1)	7.220(2)	0.151	5.301	3.882	52.36	26.81	48.89(1)	19.32(5)	83.82(4)

The standard prediction evaluation metrics have been multiplied by 100. The DA is reported in percentage terms. The *P*-values of the PT, MDM, sign and SPA tests have been multiplied by 100 and are all based on one-sided tests. Rankings are in brackets.

Table XII
The BEYR in the United States: Average returns, volatility of returns and trading profitability.

Trading strategy	Forecasting models	Total wealth	Average return	Std. dev. of returns	Sharpe ratio	Nb. of switches
B&H bonds		310.07	0.612	2.022	0.114	-
B&H equities		586.03	1.019	4.295	0.148	-
BEYR1						
I	COINT(3,2)	775.73 (750.67)	1.142 (1.124)	3.688	0.206 (0.201)	57
	ARMA(1,1)	473.08 (462.21)	0.899 (0.886)	4.116	0.126 (0.123)	40
IIA	COINT(3,2)	390.19 (388.85)	0.734 (0.732)	2.124	0.166 (0.165)	6
	ARMA(1,1)	390.19 (388.85)	0.734 (0.732)	2.124	0.166 (0.165)	6
	Naive Model	376.62 (375.31)	0.719 (0.718)	2.291	0.148 (0.147)	6
IIB	COINT(3,2)	432.66 (425.18)	0.820 (0.811)	3.278	0.134 (0.131)	30
	ARMA(1,1)	420.87 (413.14)	0.806 (0.796)	3.271	0.130 (0.127)	32
	Naive Model	340.98 (336.05)	0.707 (0.700)	3.616	0.090 (0.088)	25
IIC	ARMA(1,1)	337.43 (330.08)	0.699 (0.688)	3.570	0.089 (0.086)	38
	Naive Model	282.80 (268.48)	0.611 (0.584)	3.673	0.063 (0.055)	90
III	COINT(3,2)	556.08 (550.00)	0.947 (0.941)	3.130	0.181 (0.179)	19
	ARMA(1,1)	543.06 (537.13)	0.934 (0.929)	3.135	0.176 (0.174)	19
	Naive Model	533.12 (527.03)	0.927 (0.921)	3.223	0.169 (0.168)	20
IV	MS-Pr(>0.5)	515.24 (512.56)	0.887 (0.884)	2.407	0.210 (0.209)	9
	MS-Pr(>0.9)	465.48 (463.57)	0.832 (0.830)	2.369	0.190 (0.189)	7
BEYR2						
I	COINT(3,4)	495.46 (475.00)	0.896 (0.874)	3.406	0.151 (0.145)	73
	ARMA(1,1)	364.09 (357.43)	0.759 (0.749)	4.065	0.093 (0.090)	32
IIA	COINT(3,4)	540.52 (537.10)	0.910 (0.907)	2.354	0.225 (0.223)	11
	ARMA(1,1)	602.63 (597.45)	0.969 (0.965)	2.423	0.243 (0.241)	15
	Naive Model	639.19 (634.45)	1.001 (0.997)	2.458	0.252 (0.250)	13
IIB	COINT(3,4)	633.94 (623.09)	1.022 (1.013)	3.304	0.194 (0.191)	30
	ARMA(1,1)	609.57 (599.14)	1.005 (0.995)	3.391	0.184 (0.181)	30
	Naive Model	410.54 (405.11)	0.804 (0.797)	3.591	0.118 (0.116)	23
IIC	ARMA(1,1)	308.98 (296.40)	0.657 (0.636)	3.682	0.075 (0.069)	72
	Naive Model	381.85 (362.16)	0.767 (0.740)	3.632	0.106 (0.099)	92
III	COINT(3,4)	715.03 (704.76)	1.103 (1.096)	3.806	0.190 (0.188)	25
	ARMA(1,1)	605.18 (597.82)	1.017 (1.010)	3.833	0.166 (0.164)	21
	Naive Model	783.69 (775.69)	1.153 (1.147)	3.834	0.201 (0.200)	18
IV	MS-Pr(>0.5)	743.03 (739.22)	1.082 (1.079)	2.526	0.277 (0.276)	9
	MS-Pr(>0.9)	755.97 (749.47)	1.102 (1.097)	2.913	0.247 (0.246)	15

Figures are in percent per month. Entries in parentheses are figures net of transaction costs. Initial investment amount is 100.

Table XIII
The BEYR in the United Kingdom: Average returns, volatility of returns and trading profitability.

Trading strategy	Forecasting models	Total wealth	Average return	Std. dev. of returns	Sharpe ratio	Nb. of switches
B&H bonds		399.46	0.744	2.010	0.082	-
B&H equities		411.94	0.835	4.349	0.059	-
BEYR1						
I	COINT(3,2)	396.85 (387.36)	0.760 (0.747)	2.802	0.065 (0.060)	42
	AR(1)	294.73 (291.00)	0.595 (0.588)	2.473	0.007 (0.004)	22
IIA	COINT(3,2)	409.08 (407.42)	0.830 (0.827)	4.303	0.058 (0.058)	7
	AR(1)	445.69 (442.82)	0.872 (0.869)	4.257	0.069 (0.068)	11
	Naive Model	450.19 (447.56)	0.880 (0.877)	4.303	0.070 (0.069)	10
IIB	COINT(3,2)	653.05 (633.76)	1.049 (1.033)	3.647	0.129 (0.125)	52
	AR(1)	636.26 (621.04)	1.031 (1.019)	3.550	0.128 (0.124)	42
	Naive Model	486.88 (477.10)	0.899 (0.889)	3.771	0.085 (0.082)	35
IIC	AR(1)	362.51 (348.55)	0.717 (0.696)	2.959	0.047 (0.040)	68
	Naive Model	468.37 (441.35)	0.886 (0.855)	3.951	0.078 (0.070)	103
III	COINT(3,2)	420.82 (420.58)	0.846 (0.846)	4.347	0.062 (0.061)	1
	AR(1)	420.82 (420.58)	0.846 (0.846)	4.347	0.062 (0.061)	1
	Naive Model	411.94 (411.94)	0.835 (0.835)	4.349	0.059 (0.059)	0
IV	MS-Pr($>$ 0.5)	500.25 (498.53)	0.929 (0.927)	4.158	0.084 (0.084)	6
	MS-Pr($>$ 0.9)	445.49 (441.42)	0.864 (0.859)	4.059	0.070 (0.069)	16
BEYR2						
I	COINT(3,5)	220.31 (210.56)	0.465 (0.441)	3.212	-0.035 (-0.043)	78
	AR(1)	328.55 (326.68)	0.661 (0.658)	2.807	0.029 (0.028)	10
IIA	COINT(3,5)	438.38 (433.10)	0.847 (0.840)	3.829	0.070 (0.068)	21
	AR(1)	439.35 (435.59)	0.848 (0.843)	3.844	0.070 (0.069)	15
	Naive Model	422.56 (419.15)	0.828 (0.823)	3.840	0.065 (0.064)	14
IIB	COINT(3,5)	751.25 (728.19)	1.116 (1.099)	3.458	0.155 (0.150)	54
	AR(1)	692.78 (676.15)	1.077 (1.064)	3.574	0.139 (0.136)	42
	Naive Model	600.89 (589.52)	1.006 (0.996)	3.668	0.116 (0.114)	33
IIC	AR(1)	526.12 (503.85)	0.928 (0.906)	3.469	0.101 (0.094)	75
	Naive Model	516.62 (486.81)	0.932 (0.901)	3.832	0.092 (0.084)	103
III	COINT(3,5)	439.36 (437.59)	0.865 (0.863)	4.255	0.067 (0.067)	7
	AR(1)	439.36 (437.59)	0.865 (0.863)	4.255	0.067 (0.067)	7
	Naive Model	393.82 (392.88)	0.808 (0.807)	4.264	0.054 (0.053)	4
IV	MS-Pr($>$ 0.5)	450.82 (449.79)	0.864 (0.863)	3.907	0.073 (0.073)	4
	MS-Pr($>$ 0.9)	467.92 (466.34)	0.883 (0.881)	3.892	0.078 (0.078)	6

Figures are in percent per month. Entries in parentheses are figures net of transaction costs. Initial investment amount is 100.

Table XIV

The BEYR in the Netherlands: Average returns, volatility of returns and trading profitability.

Trading strategy	Forecasting models	Total wealth	Average return	Std. dev. of returns	Sharpe ratio	Nb. of switches
B&H bonds		296.17	0.578	1.495	0.110	-
B&H equities		500.12	0.963	4.854	0.113	-
BEYR1						
I	COINT(3,2)	395.01 (383.09)	0.789 (0.773)	3.716	0.101 (0.097)	53
	ARMA(1,1)-PGARCH(1,1)	264.29 (256.18)	0.580 (0.564)	3.752	0.044 (0.040)	54
IIA	COINT(3,2)	417.70 (415.08)	0.789 (0.785)	2.840	0.132 (0.131)	11
	ARMA(1,1)-PGARCH(1,1)	389.67 (387.23)	0.752 (0.748)	2.812	0.120 (0.119)	11
	Naive Model	293.51 (291.77)	0.616 (0.613)	3.199	0.063 (0.062)	10
IIB	COINT(3,2)	479.93 (471.23)	0.882 (0.872)	3.471	0.135 (0.132)	32
	ARMA(1,1)-PGARCH(1,1)	448.86 (441.70)	0.849 (0.841)	3.549	0.123 (0.120)	28
	Naive Model	256.22 (253.36)	0.565 (0.560)	3.790	0.040 (0.039)	19
IIC	ARMA(1,1)-PGARCH(1,1)	472.01 (462.39)	0.885 (0.874)	3.794	0.124 (0.121)	36
	Naive Model	189.70 (179.61)	0.414 (0.386)	3.935	0.000 (-0.007)	95
III	COINT(3,2)	514.18 (506.29)	0.928 (0.920)	3.726	0.138 (0.136)	27
	ARMA(1,1)-PGARCH(1,1)	515.47 (509.30)	0.933 (0.926)	3.808	0.136 (0.135)	21
	Naive Model	408.70 (404.90)	0.812 (0.807)	3.830	0.104 (0.103)	16
IV	MS-Pr($>$ 0.5)	353.83 (352.61)	0.726 (0.724)	3.552	0.088 (0.087)	6
	MS-Pr($>$ 0.9)	334.03 (332.87)	0.695 (0.693)	3.530	0.080 (0.079)	6
BEYR2						
I	COINT(3,2)	370.88 (360.76)	0.738 (0.723)	3.210	0.101 (0.097)	48
	ARMA(3,3)-GARCH(1,1)	365.53 (355.50)	0.759 (0.744)	4.001	0.086 (0.083)	48
IIA	COINT(3,2)	286.51 (285.98)	0.585 (0.585)	2.626	0.066 (0.065)	3
	ARMA(3,3)-GARCH(1,1)	285.30 (284.77)	0.583 (0.582)	2.627	0.065 (0.064)	3
	Naive Model	280.81 (280.32)	0.575 (0.574)	2.621	0.062 (0.061)	3
IIB	COINT(3,2)	452.30 (443.99)	0.848 (0.838)	3.394	0.128 (0.125)	32
	ARMA(3,3)-GARCH(1,1)	510.14 (501.93)	0.913 (0.905)	3.451	0.145 (0.142)	28
	Naive Model	307.28 (304.24)	0.649 (0.644)	3.503	0.067 (0.066)	17
IIC	ARMA(3,3)-GARCH(1,1)	544.99 (524.07)	0.964 (0.943)	3.912	0.141 (0.135)	68
	Naive Model	257.76 (244.92)	0.564 (0.537)	3.672	0.041 (0.034)	89
III	COINT(3,2)	405.76 (400.46)	0.803 (0.796)	3.707	0.105 (0.103)	23
	ARMA(3,3)-GARCH(1,1)	450.01 (445.18)	0.859 (0.853)	3.733	0.119 (0.118)	19
	Naive Model	338.54 (335.43)	0.713 (0.709)	3.840	0.078 (0.077)	16
IV	MS-Pr($>$ 0.5)	205.52 (204.94)	0.433 (0.431)	3.305	0.006 (0.005)	5
	MS-Pr($>$ 0.9)	213.53 (212.67)	0.453 (0.451)	3.297	0.012 (0.011)	7

Figures are in percent per month. Entries in parentheses are figures net of transaction costs. Initial investment amount is 100.

Table XV
The BEYR in Germany: Average returns, volatility of returns and trading profitability.

Trading strategy	Forecasting models	Total wealth	Average return	Std. dev. of returns	Sharpe ratio	Nb. of switches
B&H bonds		287.91	0.564	1.501	0.118	-
B&H equities		327.78	0.795	5.799	0.070	-
BEYR1						
I	COINT(3,2)	207.98 (197.64)	0.487 (0.460)	4.458	0.023 (0.017)	88
	ARMA(1,1)	193.52 (185.23)	0.451 (0.428)	4.498	0.014 (0.009)	76
IIA	COINT(3,2)	304.81 (302.86)	0.651 (0.647)	3.605	0.073 (0.072)	11
	ARMA(1,1)	242.78 (241.50)	0.537 (0.534)	3.740	0.040 (0.040)	9
	Naive Model	235.33 (234.10)	0.524 (0.521)	3.819	0.036 (0.035)	9
IIB	COINT(3,2)	277.37 (272.26)	0.619 (0.609)	4.070	0.057 (0.055)	32
	ARMA(1,1)	255.42 (250.71)	0.577 (0.567)	4.097	0.047 (0.044)	32
	Naive Model	176.64 (174.27)	0.405 (0.398)	4.535	0.004 (0.003)	23
IIC	ARMA(1,1)	336.68 (326.28)	0.716 (0.700)	4.033	0.082 (0.078)	54
	Naive Model	178.13 (167.77)	0.417 (0.386)	4.680	0.006 (-0.000)	104
III	COINT(3,2)	364.27 (361.54)	0.811 (0.808)	5.123	0.083 (0.082)	13
	ARMA(1,1)	363.24 (360.08)	0.811 (0.806)	5.139	0.083 (0.082)	15
	Naive Model	445.83 (442.73)	0.920 (0.916)	5.174	0.103 (0.102)	12
IV	MS-Pr($>$ 0.5)	472.75 (471.11)	0.937 (0.936)	4.914	0.112 (0.112)	6
	MS-Pr($>$ 0.9)	536.36 (532.68)	0.992 (0.989)	4.681	0.130 (0.129)	12

Figures are in percent per month. Entries in parentheses are figures net of transaction costs. Initial investment amount is 100.

Table XVI
The Equity Yield in the United States: Average returns, volatility of returns and trading profitability.

Trading strategy	Forecasting models	Total wealth	Average return	Std. dev. of returns	Sharpe ratio	Nb. of switches
B&H bonds		310.07	0.612	2.022	0.114	-
B&H equities		586.03	1.019	4.295	0.148	-
Dividend Yield						
I	COINT(3,2)	723.44 (707.71)	1.083 (1.071)	3.044	0.230 (0.226)	38
	ARMA(1,1)	413.30 (402.49)	0.789 (0.775)	3.073	0.133 (0.128)	46
IIA	COINT(3,2)	310.07 (310.07)	0.612 (0.612)	2.022	0.114 (0.114)	0
	ARMA(1,1)	310.07 (310.07)	0.612 (0.612)	2.022	0.114 (0.114)	0
	Naive Model	310.07 (310.07)	0.612 (0.612)	2.022	0.114 (0.114)	0
IIB	COINT(3,2)	355.56 (348.27)	0.716 (0.705)	3.246	0.103 (0.100)	36
	ARMA(1,1)	356.64 (350.54)	0.718 (0.709)	3.278	0.103 (0.100)	30
	Naive Model	309.60 (305.72)	0.642 (0.636)	3.216	0.081 (0.079)	22
IIC	ARMA(1,1)	313.55 (311.90)	0.657 (0.655)	3.463	0.080 (0.079)	9
	Naive Model	279.71 (263.76)	0.602 (0.571)	3.569	0.062 (0.053)	102
III	COINT(3,2)	394.39 (391.87)	0.761 (0.758)	2.969	0.128 (0.127)	11
	ARMA(1,1)	435.63 (431.37)	0.813 (0.808)	2.955	0.146 (0.144)	17
	Naive Model	409.13 (406.07)	0.783 (0.779)	3.034	0.132 (0.131)	13
IV	MS-Pr($>$ 0.5)	391.44 (391.22)	0.735 (0.735)	2.109	0.168 (0.168)	1
	MS-Pr($>$ 0.9)	391.44 (391.22)	0.735 (0.735)	2.109	0.168 (0.168)	1
Earnings Yield						
I	COINT(3,4)	424.06 (410.14)	0.796 (0.779)	2.845	0.146 (0.140)	58
	ARMA(1,1)	225.51 (221.13)	0.494 (0.483)	3.685	0.030 (0.028)	34
IIA	COINT(3,2)	310.07 (310.07)	0.612 (0.612)	2.022	0.114 (0.114)	0
	ARMA(1,1)	310.07 (310.07)	0.612 (0.612)	2.022	0.114 (0.114)	0
	Naive Model	310.07 (310.07)	0.612 (0.612)	2.022	0.114 (0.114)	0
IIB	COINT(3,4)	508.98 (499.15)	0.902 (0.892)	3.195	0.163 (0.160)	34
	ARMA(1,1)	515.95 (504.28)	0.909 (0.897)	3.185	0.166 (0.162)	40
	Naive Model	412.47 (403.08)	0.792 (0.780)	3.204	0.128 (0.125)	40
IIC	ARMA(1,1)	401.24 (391.93)	0.801 (0.788)	3.850	0.109 (0.106)	41
	Naive Model	370.48 (347.77)	0.759 (0.725)	3.824	0.099 (0.090)	110
III	COINT(3,4)	815.07 (807.10)	1.143 (1.138)	2.969	0.257 (0.255)	17
	ARMA(1,1)	883.16 (871.59)	1.188 (1.182)	3.082	0.262 (0.260)	23
	Naive Model	893.52 (885.81)	1.194 (1.190)	3.070	0.265 (0.263)	15
IV	MS-Pr($>$ 0.5)	415.77 (415.54)	0.765 (0.765)	2.035	0.189 (0.189)	1
	MS-Pr($>$ 0.9)	415.77 (415.54)	0.765 (0.765)	2.035	0.189 (0.189)	1

Figures are in percent per month. Entries in parentheses are figures net of transaction costs. Initial investment amount is 100.

Table XVII
The Equity Yield in the United Kingdom: Average returns, volatility of returns and trading profitability.

Trading strategy	Forecasting models	Total wealth	Average return	Std. dev. of returns	Sharpe ratio	Nb. of switches
B&H bonds		399.46	0.744	2.010	0.082	-
B&H equities		411.94	0.835	4.349	0.059	-
Dividend Yield						
I	COINT(3,2)	508.20 (501.24)	0.875 (0.868)	2.250	0.132 (0.129)	24
	AR(1)	334.70 (332.40)	0.716 (0.713)	4.117	0.034 (0.033)	12
IIA	COINT(3,2)	437.93 (436.44)	0.796 (0.794)	2.179	0.100 (0.099)	6
	AR(1)	437.93 (436.44)	0.796 (0.794)	2.179	0.100 (0.099)	6
	Naive Model	409.44 (407.81)	0.764 (0.762)	2.368	0.078 (0.069)	7
IIB	COINT(3,2)	438.41 (429.93)	0.832 (0.821)	3.439	0.074 (0.071)	34
	AR(1)	412.21 (405.12)	0.805 (0.796)	3.587	0.063 (0.060)	30
	Naive Model	321.98 (316.81)	0.679 (0.671)	3.691	0.027 (0.025)	28
IIC	AR(1)	346.31 (344.52)	0.742 (0.739)	4.295	0.038 (0.037)	9
	Naive Model	344.37 (325.47)	0.725 (0.695)	3.966	0.037 (0.029)	98
III	COINT(3,2)	445.11 (440.76)	0.846 (0.841)	3.624	0.074 (0.072)	17
	AR(1)	476.71 (472.63)	0.883 (0.878)	3.637	0.084 (0.082)	15
	Naive Model	459.52 (455.59)	0.859 (0.835)	3.631	0.078 (0.077)	15
IV	MS-Pr($>$ 0.5)	440.52 (439.73)	0.818 (0.817)	2.919	0.082 (0.082)	3
	MS-Pr($>$ 0.9)	437.13 (436.34)	0.814 (0.813)	2.919	0.081 (0.080)	3
Earnings Yield						
I	COINT(3,5)	324.82 (312.63)	0.649 (0.629)	2.583	0.027 (0.020)	66
	AR(1)	396.18 (394.37)	0.802 (0.800)	4.061	0.055 (0.054)	8
IIA	COINT(3,5)	399.46 (399.46)	0.744 (0.744)	2.010	0.082 (0.082)	0
	AR(1)	399.89 (399.44)	0.745 (0.744)	2.011	0.083 (0.082)	2
	Naive Model	397.40 (396.73)	0.741 (0.740)	2.005	0.081 (0.081)	3
IIB	COINT(3,5)	498.20 (488.61)	0.896 (0.886)	3.372	0.094 (0.091)	34
	AR(1)	428.45 (422.62)	0.819 (0.812)	3.427	0.070 (0.068)	24
	Naive Model	369.60 (364.07)	0.748 (0.740)	3.596	0.047 (0.045)	26
IIC	AR(1)	497.63 (485.25)	0.925 (0.911)	4.132	0.084 (0.081)	44
	Naive Model	330.30 (313.62)	0.704 (0.677)	3.989	0.031 (0.025)	90
III	COINT(3,5)	432.59 (428.84)	0.828 (0.823)	3.509	0.071 (0.070)	15
	AR(1)	513.47 (509.63)	0.919 (0.915)	3.559	0.096 (0.095)	13
	Naive Model	474.38 (470.84)	0.881 (0.877)	3.641	0.083 (0.082)	13
IV	MS-Pr($>$ 0.5)	443.55 (442.26)	0.820 (0.818)	2.846	0.085 (0.084)	5
	MS-Pr($>$ 0.9)	405.31 (404.58)	0.772 (0.771)	2.848	0.068 (0.068)	3

Figures are in percent per month. Entries in parentheses are figures net of transaction costs. Initial investment amount is 100.

Table XVIII
The Equity Yield in the Netherlands: Average returns, volatility of returns and trading profitability.

Trading strategy	Forecasting models	Total wealth	Average return	Std. dev. of returns	Sharpe ratio	Nb. of switches
B&H bonds		296.17	0.578	1.495	0.110	-
B&H equities		500.12	0.963	4.854	0.113	-
Dividend Yield						
I	COINT(3,2)	561.73 (539.82)	0.952 (0.931)	3.091	0.174 (0.167)	69
	ARMA(1,1)-PGARCH(1,1)	454.00 (438.43)	0.866 (0.848)	3.822	0.118 (0.114)	60
IIA	COINT(3,2)	323.89 (323.17)	0.627 (0.626)	1.609	0.133 (0.132)	4
	ARMA(1,1)-PGARCH(1,1)	323.89 (323.17)	0.627 (0.626)	1.609	0.133 (0.132)	4
	Naive Model	356.64 (355.64)	0.680 (0.679)	1.800	0.148 (0.148)	5
IIB	COINT(3,2)	277.50 (273.06)	0.592 (0.584)	3.399	0.053 (0.050)	28
	ARMA(1,1)-PGARCH(1,1)	255.49 (250.25)	0.552 (0.541)	3.485	0.040 (0.037)	36
	Naive Model	143.07 (141.41)	0.259 (0.253)	3.729	-0.041 (-0.043)	20
IIC	ARMA(1,1)-PGARCH(1,1)	433.65 (424.27)	0.849 (0.837)	4.007	0.109 (0.106)	38
	Naive Model	205.79 (193.63)	0.447 (0.415)	3.708	0.009 (0.000)	106
III	COINT(3,2)	188.10 (186.49)	0.397 (0.392)	3.597	-0.005 (-0.006)	15
	ARMA(1,1)-PGARCH(1,1)	196.58 (195.13)	0.420 (0.416)	3.611	0.002 (0.001)	13
	Naive Model	209.43 (208.12)	0.455 (0.452)	3.659	0.011 (0.010)	11
IV	MS-Pr($>$ 0.5)	171.44 (171.13)	0.336 (0.335)	3.238	-0.024 (-0.024)	3
	MS-Pr($>$ 0.9)	167.16 (166.85)	0.323 (0.322)	3.230	-0.028 (-0.028)	3
Earnings Yield						
I	COINT(3,2)	540.85 (524.28)	0.923 (0.907)	2.799	0.182 (0.176)	54
	ARMA(3,3)-GARCH(1,1)	476.93 (458.52)	0.908 (0.887)	4.206	0.118 (0.113)	68
IIA	COINT(3,2)	296.17 (296.17)	0.578 (0.578)	1.495	0.110 (0.110)	0
	ARMA(3,3)-GARCH(1,1)	322.71 (322.36)	0.625 (0.624)	1.599	0.132 (0.132)	2
	Naive Model	296.17 (296.17)	0.578 (0.578)	1.495	0.110 (0.110)	0
IIB	COINT(3,2)	352.55 (347.28)	0.718 (0.710)	3.409	0.089 (0.087)	26
	ARMA(3,3)-GARCH(1,1)	337.35 (331.13)	0.699 (0.689)	3.520	0.081 (0.078)	32
	Naive Model	246.35 (242.94)	0.532 (0.525)	3.460	0.034 (0.032)	24
IIC	ARMA(3,3)-GARCH(1,1)	558.03 (543.46)	0.991 (0.977)	4.237	0.136 (0.133)	46
	Naive Model	189.47 (180.32)	0.401 (0.375)	3.619	-0.004 (-0.011)	86
III	COINT(3,2)	201.86 (199.68)	0.430 (0.425)	3.501	0.005 (0.003)	19
	ARMA(3,3)-GARCH(1,1)	180.36 (178.40)	0.374 (0.368)	3.567	-0.011 (-0.013)	19
	Naive Model	162.08 (160.51)	0.319 (0.314)	3.595	-0.026 (-0.028)	17
IV	MS-Pr($>$ 0.5)	236.90 (236.50)	0.499 (0.498)	3.062	0.028 (0.028)	3
	MS-Pr($>$ 0.9)	232.04 (231.65)	0.488 (0.487)	3.051	0.024 (0.024)	3

Figures are in percent per month. Entries in parentheses are figures net of transaction costs. Initial investment amount is 100.

Table XIX

The Equity Yield in Germany: Average returns, volatility of returns and trading profitability.

Trading strategy	Forecasting models	Total wealth	Average return	Std. dev. of returns	Sharpe ratio	Nb. of switches
B&H bonds		287.91	0.564	1.501	0.118	-
B&H equities		327.78	0.795	5.799	0.070	-
Dividend Yield						
I	COINT(3,2)	300.69 (292.53)	0.629 (0.614)	3.260	0.074 (0.070)	48
	ARMA(1,1)	211.16 (202.57)	0.480 (0.459)	4.167	0.023 (0.017)	72
IIA	COINT(3,2)	291.39 (291.06)	0.582 (0.581)	2.165	0.090 (0.090)	2
	ARMA(1,1)	289.94 (289.27)	0.579 (0.578)	2.166	0.089 (0.089)	4
	Naive Model	314.22 (313.33)	0.624 (0.622)	2.279	0.104 (0.104)	5
IIB	COINT(3,2)	299.56 (294.37)	0.661 (0.651)	4.070	0.067 (0.065)	30
	ARMA(1,1)	266.18 (261.56)	0.598 (0.589)	4.078	0.052 (0.050)	30
	Naive Model	200.49 (197.25)	0.471 (0.462)	4.544	0.019 (0.017)	28
IIC	ARMA(1,1)	215.53 (210.29)	0.503 (0.490)	4.436	0.026 (0.023)	43
	Naive Model	170.28 (160.74)	0.394 (0.364)	4.699	0.002 (-0.005)	100
III	COINT(3,2)	218.95 (216.32)	0.506 (0.499)	4.316	0.028 (0.026)	21
	ARMA(1,1)	232.58 (230.06)	0.538 (0.532)	4.330	0.035 (0.034)	19
	Naive Model	199.33 (197.38)	0.467 (0.462)	4.528	0.018 (0.017)	12
IV	MS-Pr($>$ 0.5)	183.87 (183.34)	0.392 (0.391)	3.755	0.002 (0.001)	5
	MS-Pr($>$ 0.9)	175.55 (175.04)	0.367 (0.365)	3.730	-0.005 (-0.006)	5

Figures are in percent per month. Entries in parentheses are figures net of transaction costs. Initial investment amount is 100.

Table XX

Trading Performance of Models and Strategies: A Summary.

	BEYR				Equity Yield			
Models and Strategies	US	UK	NL	GE	US	UK	NL	GE
Naive Model	=	+	- - -	- - -	-	–	- - -	- - -
SBP Model	+	=	+++	- -	-	+	=	- - -
COINT Model	+++	=	=	-	+	++	=	- -
MS-Pr Model = Strategy IV	+++	=	- - -	+	+++	++	-	- - -
Strategy III	+++	=	=	=	++	++	- - -	- - -
Strategy IIC	- - -	+	=	-	- - -	- - -	- - -	- - -
Strategy IIB	=	+++	++	- - -	- -	=	- - -	- - -
Strategy IIA	+++	=	- -	- -	=	++	++	=
Strategy I	=	- - -	- - -	- - -	=	- - -	+++	-

A '+++' ('- - -') means that the model or strategy under review is superior (inferior) to the two buy-and-hold portfolios in more than two-thirds of cases . A '++' ('- -') means that the model or strategy is superior (inferior) to the two buy-and-hold portfolios in more than 50% of cases *and* that it is never inferior (superior) to the two buy-and-hold portfolios in more than one-third of cases. A '+' ('-') means that the model or strategy is superior (inferior) to the two buy-and-hold portfolios in more than one-third of cases *and* that it is never inferior (superior) to the two buy-and-hold portfolios in more than one-third of cases. A '=' includes all other cases.

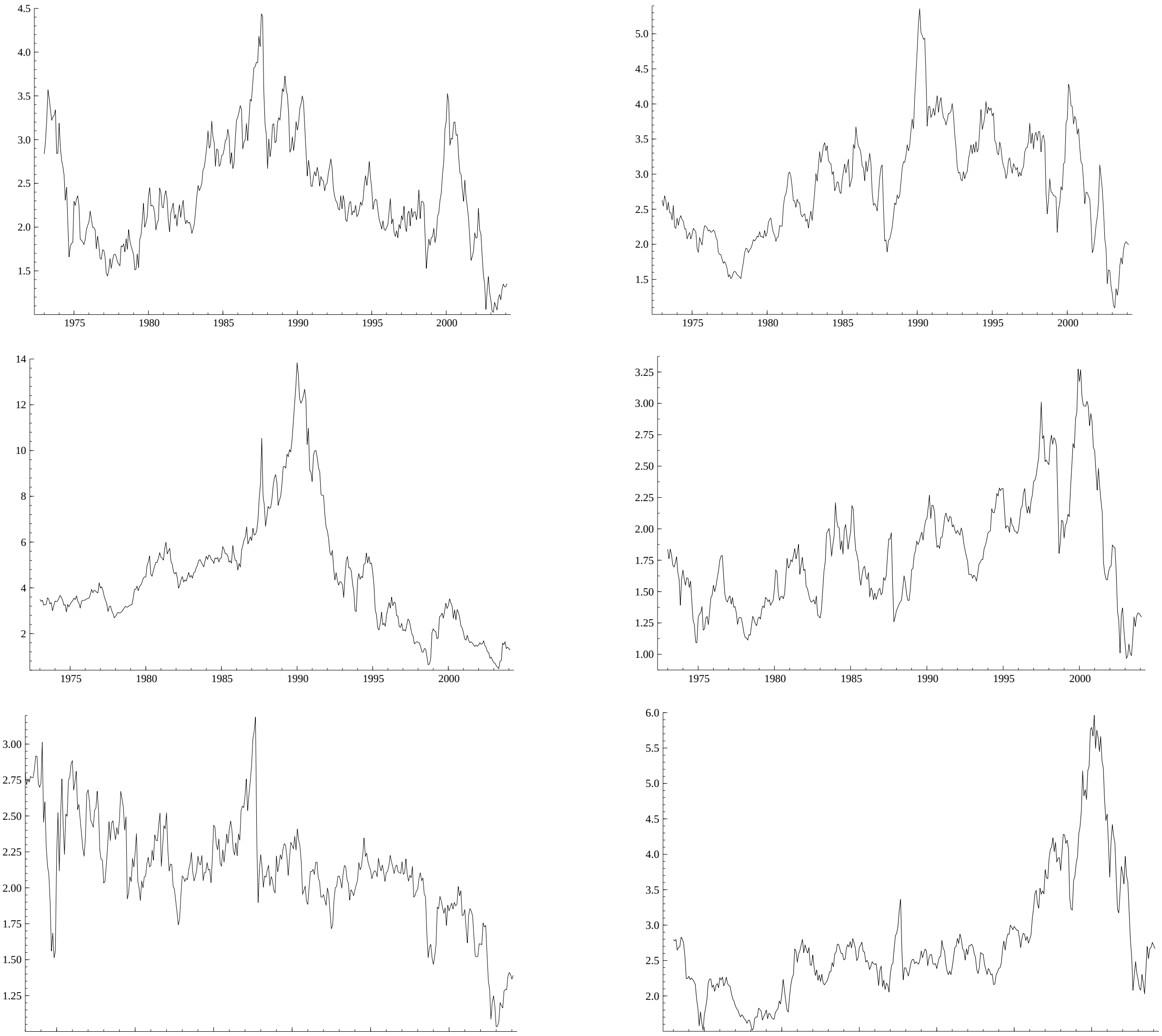

Figure 1. The Bond-Dividend Yield Ratio. From top left to bottom right: France, Germany, Japan, the Netherlands, the UK, and the US.

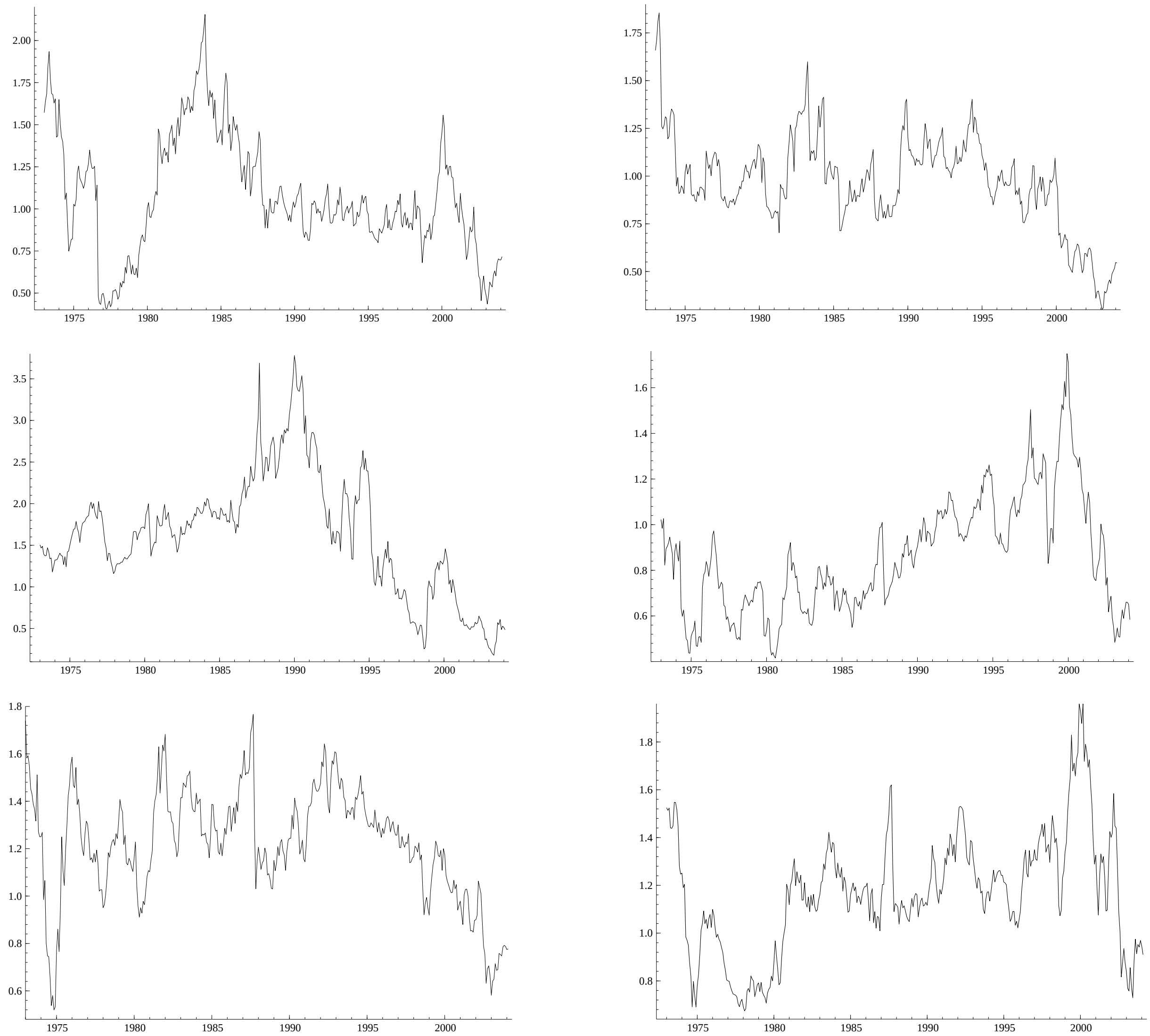

Figure 2. The Bond-Earnings Yield Ratio. From top left to bottom right: France, Germany, Japan, the Netherlands, the UK, and the US.