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The information content of the Bond-Equity Yield Ratio: Better than a random walk?

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ABSTRACT

Since the 1990's run up in stock prices and subsequent crashes, the financial community has taken a dim view of the traditional valuation ratios and has instead turned its attention to a new valuation ratio: the Bond-Equity Yield Ratio (BEYR). In this paper we provide the first comprehensive, both in-sample and out-of-sample, statistical assessment of the fundamental short-term reversion dynamics of the BEYR towards its long-term mean. Using cointegrated VAR models, we show that the BEYR can depart from its long-term relationship for an extended period of time before reversion process finally brings it back to equilibrium. The out-of-sample forecasting analysis, based on both equally and superior predictive ability tests, shows that the cointegrated VAR model does not perform better than a naive random walk. As such, we cast doubt on the ability of the BEYR to predict monthly stock return.

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1. Introduction

Since the sustained 1990's run up in stock prices, there has been growing skepticism among academics about the predictive ability of traditional valuation ratios (TVR), such as the dividend-price (D/P) and price-earnings (P/E) ratios (Goyal and Welch, 2006). Because these ratios are highly persistent and can move far outside their historical range, linear model specifications suggest that stock prices can substantially deviate from their fundamental values over extended periods of time. This also questions the Campbell and Shiller (2001) view that TVR are substantially driven by mean reversion. In addition, stock market participants have experienced so much exhilaration and disappointment during the last decade that many of them have lost faith in the ability of TVR to correctly appraise the current state of stock markets. As a result, the financial community has recently turned its attention to an 'augmented' valuation ratio, the Bond-Equity Yield Ratio (BEYR).[1]

The BEYR is defined as the ratio of the long-term government bond market yield to the stock market yield. In the extant literature, the bond and stock market yields are respectively approximated by the yield-to-maturity on long-term government bonds (R) and by the equity yield of the most representative stock index. The two most widely used proxies for the equity yield are the dividend yield (D/P) and the earnings yield (E/P). In the traditional formulation of the BEYR, the dividend yield, instead of the earnings yield, is used as a proxy for the yield of the stock market. This is justified on the grounds that cash dividends are unambiguous. Dividend payout policies are nevertheless strongly sensitive to regulatory and taxation changes.[2] Although earnings may be prone to balance-sheet and income statements embellishments,[3] the mistaken beliefs that investors might have about their forecasts of earnings can produce post-earnings drift, short-run momentum, long-run mean reversion and earnings-price ratios that help forecast future returns (Barberis, Shleifer, and Vishny, 1998).

[1] This ratio is better known as the Gilt-Equity Yield Ratio (GEYR) in the UK. Berge and Ziemba (2006) call it the Bond Stock Earnings Yield Differential (BSEYD). As Section 2.3 indicates, the so-called 'Fed model' is a straightforward variant of the BEYR.

[2] 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. 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.

[3] 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.

To reflect the importance of both dividends and earnings, we consider two versions of the BEYR in our empirical analysis. In the first case, the BEYR takes the dividend yield as input. In the alternative specification, it features the earnings yield.[4] By relying upon bond yields (R) *and* TVR (E/P or D/P), the current BEYR is argued to exhibit enhanced predictive power for forecasting future stock returns.[5] Proponents of this approach argue that the BEYR fluctuates around a long-run equilibrium level, and that deviations from this 'central value' point to unsustainable equity prices. If the BEYR becomes high relative to its long-run level, equities are viewed as being expensive relative to bonds. The expectation, then, is that for given levels of bond yields, equity yields must rise, which will occur via a fall in equity prices. Similarly, if the BEYR is well below its long-run level, bonds are considered expensive relative to stocks, and by the same analysis, the price of the latter is expected to increase. Thus, in its crudest form, an equity trading rule based on the BEYR would say, 'if the BEYR is low, buy equities; if the BEYR is high, sell equities' (Brooks and Persand, 2001).

Some papers do find that the differential between bond and equity yields display some predictive ability in forecasting stock returns (Shen, 2003; Asness, 2003; Berge and Ziemba, 2006; ap Gwilym, Seaton, Suddason, and Thomas, 2006). However, their econometric methodology is often flawed. They suffer from at least one of the following shortcomings: no statistical correction for small-sample bias, data mining, and/or overlapping observations; no statistical and/or economic analysis of out-of-sample predictive power.[6] For instance, ap Gwilym, Seaton, Suddason, and Thomas (2006) use OLS predictive regression models but do not address the related econometric issues. In these models, real (excess) stock returns are regressed on a variable thought to potentially explain future movements in stock prices. When the predictive variable is persistent (as the BEYR and TVR are), innovations in the predictor are highly correlated with returns, as indicated by Stambaugh (1999), Lewellen (2004), or Moon, Rubia, and Valkanov (2006). Hence, the distribution of the t-statistic for the predictive variable's slope estimate can be severely affected and any inference becomes challenging: basing

[4] Switching to logs, we have that $ln(BEYR) = ln(R) - ln(D) + ln(P)$, or $beyr = r - d + p$ in the first case. In the alternative specification, we have $beyr = r - e + p$. Readers familiar with the cointegration framework will recognize that proponents of the BEYR ratio state that r, p, and d (or e) are cointegrated with 'constrained' weights for the long-term relationship set equal to (1,-1,1).

[5] See Clare, Thomas, and Wickens (1994), Levin and Wright (1998), Harris and Sanchez-Valle (2000), and Brooks and Persand (2001) for early discussions and empirical applications.

[6] Giot and Petitjean (2006) provides a discussion of these econometric pitfalls.

inferences on standard asymptotic results can therefore lead to considerable size distortions when testing the null hypothesis of no predictability.

This paper takes a different tack to assess the predictive ability of the BEYR. First, we do not employ OLS predictive regressions and avoid the econometric pitfalls that characterize these regressions. Second, we do not search for an enhanced model specification that would allow valuation ratios to exhibit either similar dynamics around a broken trend (Carlson, Pelz, and Wohar, 2002; Rapach and Wohar, 2006b) or distinct dynamics around a constant long-run equilibrium level (Ackert and Hunter, 1999; Madsen and Milas, 2005; Coakley and Fuertes, 2006). Although some of these models succeed in showing how traditional valuation ratios are overall mean-reverting despite their persistent behavior, specification search is a serious issue. When more sophisticated models are explored, some of these models are indeed bound to work both in-sample and out-of-sample by pure chance (Goyal and Welch, 2006).

In contrast, we stick to the original, well-established framework of cointegration that has been commonly used in the past to examine the reversion dynamics displayed by TVR. In the extant empirical literature, TVR are mostly found not to exhibit mean reversion as the unit root null cannot be rejected using the ADF test (Timmermann, 1995; Lamont, 1998; Balke and Wohar, 2001; Coakley and Fuertes, 2006).[7] The failure to reject the null can be explained by the fact that, while TVR cross their sample averages quite often, they do it at intervals which can go beyond several years. Such lack of mean-reversion in TVR suggests that prices and dividends (or earnings) may randomly drift apart in the long run or, equivalently, that they may not cointegrate.[8] Even when evidence of cointegration is found, the adjustment dynamics is very slow, casting doubt on the ability of TVR to forecast stock price changes.

Cointegrated VAR (or VECM) models allow an indirect assessment of the predictive power of the BEYR. We can indeed test for the presence of reversion dynamics in the BEYR as well as evaluate the magnitude and significance of these dynamics. In this paper, we estimate the cointegration model for six countries, using monthly data from January 1973 to January 2004. We proceed in three steps. First, we test for the presence of a long-run relationship between

[7] Campbell and Shiller (2001) attribute such a finding to the poor properties (low power) of the ADF and related linear tests in the context of slowly mean-reverting processes.

[8] The early paper of Campbell and Shiller (1987) did not get meaningful cointegration results (using stock prices and dividends as input variables). MacDonald and Power (1995) validate the present value relationship between earnings and stock prices for the U.S. market. More recently, the international analysis conducted by Harasty and Roulet (2000) also supports the cointegration hypothesis.

bond yields, prices, and dividends (or earnings). If there is no evidence of cointegration, there is no monthly reversion dynamics in the BEYR towards its long-run equilibrium: bond yields, prices, and dividends (or earnings) randomly drift apart in the long run. When evidence of cointegration is found, we study the magnitude and statistical significance of the monthly reversion dynamics displayed by the BEYR. In particular, we investigate whether a deviation from the long-run equilibrium impacts stock prices such that the BEYR reverts to its long-run equilibrium. Finally, we test for the significance of the government bond yield in the long-run relationship. If significance is found, the long-term bond yield bears on long-term stock market valuations. In this case, bond yields play a significant economic role in the analysis and should be considered when assessing stock returns over the long-run. While the in-sample estimation of the cointegration model in this paper follows much of the extant literature, we let the empirical analysis choose the optimal long-term coefficients in the cointegrating relationship. We then test if these optimal weights are equal to the constrained weights assumed by the BEYR. In contrast, Mills (1991), Harris and Sanchez-Valle (2000), and Koivu, Pennanen, and Ziemba (2005) do not run a complete cointegration analysis as they constrain the coefficients of the long-term relationship.

The reversion dynamics of the BEYR, possibly revealed by the in-sample estimation of the cointegration model, may still not be powerful enough to reject the argument that the BEYR does not fundamentally differ from a random walk in the short run. If the cointegration model cannot generate more accurate out-of-sample forecasts of the BEYR than a naive random walk, there is no reason to believe that the BEYR is a good predictor of short-term stock returns. Put differently, who would trust a predictive variable that is best modeled in the short run by a random walk? The short-term practical use of the BEYR would be severely limited indeed. To evaluate the short-term out-of-sample ability of the BEYR to revert to its long-run equilibrium value, we compute one-month ahead out-of-sample forecasts of the BEYR delivered by the multivariate cointegration framework. We also forecast the BEYR by using the competing ARMA-GARCH univariate methodology that has been shown to be helpful in modeling persistent processes (Stambaugh, 1999; Lewellen, 2004). We measure the short-term statistical predictive power of these models against the random walk by applying equally and superior predictive ability tests, including the Hansen (2005) test.

Our cointegration analysis shows that the BEYR exhibits a slow reversion dynamics to its long-run equilibrium at the monthly horizon. First, no evidence of cointegration is found for two countries (out of six), rejecting the whole idea that the BEYR can be used for predicting stock returns in these countries. Second, when evidence of cointegration is found, it is difficult to determine whether the BEYR features more information than the price-earnings or price-dividend ratios. This casts doubt on the need to consider bond yields in determining the 'equilibrium' stock market valuation. Third, the small absolute values of the adjustment speed coefficients point to a slow dynamical reversion process in the BEYR. Overall, the in-sample estimation of the cointegration model reveals mixed evidence of reversion dynamics in the BEYR.

Our out-of-sample analysis shows that the slow reversion dynamics of the BEYR towards its long-run equilibrium is insufficient to reject the hypothesis that the BEYR follows a random walk at the monthly horizon. Indeed, the cointegration model cannot generate more accurate monthly out-of-sample forecasts of the BEYR than a naive random walk. When assessed according to the standard error metrics, the random walk ranks first or second in each country and in almost all cases. The Modified Diebold and Mariano (MDM) test shows that the null hypothesis of equal predictive ability (EPA) between the random walk and the cointegration model is rejected in quite a few cases, suggesting that the former outperforms the later. Although the null hypothesis of EPA is rejected less often in the Sign test than in the MDM test at the 5% level, the earlier conclusions are not altered. Finally, the Hansen (2005) SPA test shows that 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. All in all, our statistical analysis of the BEYR casts doubt on its ability to be anything else than a random walk. As such it is probably a rather dubious valuation ratio that could 'predict' future stock returns as some market practitioners claim.

The rest of the paper is structured as follows. Section 2 identifies the pros and cons of the BEYR approach. It also discusses the issue related to the near persistence of valuation ratios. The dataset is presented in Section 3. The cointegration multivariate framework and the the alternative univariate approaches are detailed in Section 4. We also explain how the out-of-sample forecasts of the BEYR are evaluated from the statistical perspective. The empirical application is discussed in Section 5. We conclude in Section 6.

2. The pros and cons and the BEYR approach

The BEYR approach consists in comparing the current long-term nominal market bond yield to the stock market's equity yield (either the earnings yield, E/P, or the dividend yield, D/P). The 'mean-reverting' rationale can be described as follows. Let us assume a fall in inflation. As the nominal bond yield falls, the present value of future cash flows from equities rises, which implies a rise in stock prices and a fall in the equity yield. In other words, following a fall in nominal bond yields, stocks become relatively more attractive and their prices rise; as stock prices go up, the equity yield falls, so that bond yields look attractive again. In other words, a fall in bond yields drives the BEYR down, away from its long-run equilibrium, but the subsequent fall in equity yield drives it up, back to its long-term value.

There are pros and cons of the BEYR approach. Critics argue that the rationale underlying the BEYR is weak, even flawed, from a theoretical point of view. First, the BEYR approach can be viewed as a simplified interpretation of the present value model. Second, it makes restrictive assumptions regarding the role of inflation and monetary illusion. Durré and Giot (2006) extensively discuss these issues in a recent paper. In spite of the shaky theoretical foundations of the BEYR, proponents underline its strong relevance as an empirical description of stock prices. In particular, they view the BEYR as an 'augmented' TVR, which not only takes stock yields into account but also compares them to bond yields. The poor predictive power of TVR found in recent empirical studies further signals the need to consider bond yields when assessing stock returns. We focus on this argument in the empirical application.

2.1. A simplified interpretation of the present value model

The present value model à la Gordon-Shapiro helps to better understand the implications of the rationale underlying the BEYR.[9] In this 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, g is the expected long-term earnings growth rate, π is the risk premium, and r_f is the 'risk-free' rate.[10]

Two effects shape the relationship between stock prices and bond yields in this model. First, the discount rate effect acts through the cost of equity (K_e). Because K_e depends on the prevailing interest rate, rising (falling) bond yields 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 risk premium do *not* offset the bond yield changes).

Second, the cash-flow effect 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 points to a positive correlation between stock prices and bond yields. As inflation rises (falls) together with bond yields, the growth of future *nominal* cash flow from equities also rises (falls), which drives stock prices up (down). The underlying economic logic is that upward (downward) earnings revisions are bound to occur in economic up (down) cycles when inflation and interest rates are rising (falling).

The 'mean'-reverting argument implied by the BEYR requires that a fall (rise) in nominal bond yields must lead to a rise (fall) in stock prices, hence to a fall (rise) in the equity yield. There must exist a substitution effect between stocks and bonds which is strongly shaped by

[9]We do not consider time-varying risk premium models à la Campbell and Shiller (1988, 1989) since the BEYR approach focuses on the contemporaneous long-run relationship between stock prices, earnings (or dividends) and long-term bond yields. In this respect, the methodology is closer to Harasty and Roulet (2000) and to what some market practitioners would like to test.

[10]r_f is assumed to reflect 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 relationship of the equity yield to the bond yield. This implies, in turn, that stock prices and bond yields must be, on average, negatively correlated. Overall, the discount rate effect must dominate the cash flow effect.[11]

Little consensus has emerged in the literature focusing on the relationship between stock prices and bond yields. Some authors do find that stock prices and bond yields are negatively correlated, implying that the discount rate effect dominates. For example, using a dynamic present value model and a long sample of annual U.S. data, Beltratti and Shiller (1992) report a 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.[12] 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.[13]

The risk premium demanded by investors also varies with the state of the economy. It usually decreases during economic up cycles and increases during economic down 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).

All in all, the discount rate and cash flow effects are likely to be dependent, but it is difficult to determine which effect dominates. The overall picture is further complicated by possibly

[11] It need not follow that the discount rate and cash flow effects are independent. For instance, a positive (negative) discount rate effect on stock prices can be accompanied by a negative (positive) cash-flow effect when inflation falls (rises). Nevertheless, the cash flow effect must not offset the discount rate effect.

[12] The concept of state-dependency in stock and bond co-movements was first theoretically developed by Barsky (1989).

[13] 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 (2005), Scruggs and Glabadanidis (2003) and Connolly, Stivers, and Sun (2005), among others.

state-dependent co-movements in bond and stock prices, as well as by a time-varying risk premium (at least on a short-term basis). There is nevertheless no QED proof that the BEYR approach is flawed.

2.2. The role of money illusion and inflation

By comparing a nominal variable (bond yield) to a real one (equity yield), the BEYR approach assumes that investors suffer from the error of money illusion and/or demand different expected real expected returns when inflation changes. Money illusion means that investors would wrongly (or irrationally) set the market's equity yield as a positive function of inflation and nominal interest rates. However, there may be rational reasons for these 'expectational errors' (Modigliani and Cohn, 1979; Ritter and Warr, 2002; Siegel, 2002). For instance, inflation might positively affect the equity yield because of distorted corporate earnings and capital gain taxes in inflationary times (Asness, 2003). As a consequence, investors taste for equity risk may change with inflation, implying a time varying risk premium. They may demand lower expected returns when inflation is low, setting the equity yield at a lower level. Conversely, when inflation is high, investors demand a higher risk premium, higher expected stock returns and thus a higher equity yield.

This is at odds with most of the empirical evidence that shows that equities could be a good hedge against inflation (Marshall, 1992; Boudoukh and Richardson, 1993; Anari and Kolari, 2001; Spyrou, 2004). Nevertheless, even without the distortions above, there is no QED proof that E/P is a purely real quantity with expected real earnings growth independent of steady-state inflation. In fact, Thomas (2005) argues that forward earnings yield should vary with expected inflation. He contends that accounting earnings include inflation holding gains, which introduces a link between expected earnings and inflation. The direct comparison of bond and earnings yields would therefore make sense.

2.3. A valuable practical tool

While the BEYR approach is of limited theoretical value, it has been quite successful as an empirical description of past stock prices (Lander, Orphanides, and Douvogiannis, 1997; Asness, 2003; Campbell and Vuolteenaho, 2004). The pure 'mechanical' relationship implied by the BEYR is appealing for intuitive reasons. First, market participants constantly arbitrage the stock and bond markets. They do allocate financial resources between equities and long-term bonds by actively comparing the respective bond and stock market yields. To engage in such an operation, market participants believe in the 'substitution effect' between stocks and bonds. Second, market participants do take advantage of low interest rates to buy stocks on margin through 'carry trade' operations. Stock markets indirectly benefit from a low-rate environment as portfolio managers incur low borrowing costs when buying shares. When interest rates rise, these portfolio managers sell their shares to put a cap on their rising borrowing costs.

The so-called 'Fed Model' is the most popular application of the the rationale underlying the BEYR.[14] Widely popularized in the United States by market practitioners and finance journals, The Fed model states that the 10-year government bond yield should be inversely related to the expected earnings yield of the S&P500 index. In the Fed model, the equity yield is proxied by the anticipated earnings yield. 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. For these reasons, many practitioners view the BEYR as an augmented valuation ratio, which not only takes stock yields into account but also compares them to bond yields. The poor predictive power of TVR found in recent studies would further signal the need to consider bond yields when assessing stock returns.

2.4. The near persistence of valuation ratios

A number of studies have documented the relationship between equity returns and TVR, such as the dividend-price and price-earnings ratios. Seminal papers, including Fama and French (1988), Campbell and Shiller (1988, 1989, 1998), and Goetzmann and Jorion (1993), show that dividend yields can forecast equity market returns. Campbell and Shiller (1988, 1989) show that the earnings yield can forecast future returns as well.[15]

[14] Recent modifications of the Fed model include the "Stock Valuation Models #2" (SVM-2) introduced by Yardeni (2003). See Asness (2003) and Thomas (2005) for a discussion of the Fed model.

[15] All these seminal papers suffer from at least one of the following shortcomings: no statistical correction for the small-sample bias and/or overlapping observations; no statistical and/or economic analysis of out-of-sample predictive power.

In contrast with these empirical findings, various simple efficient-market models imply that no valuation ratio has the ability to forecast movements in stock prices, since they are not predictable. If the random-walk theory is not to imply that the valuation ratio will move beyond its historical range or get stuck at extremes forever, it therefore requires that the valuation ratio predicts future growth in the valuation variable itself. In other words, valuation ratios should be useful in forecasting future dividend or earnings growth. For example, high prices relative to dividends (i.e. a low dividend-price ratio) must forecast unusual increases in dividends, declines (at least, unusually slow growth) in prices, or a combination of both. Since stock prices are unpredictable in the random-walk theory, the dividend-price ratio must forecast unusual increases in dividends.

Campbell and Shiller (2001) argue that the dividend-price ratio only weakly predicts dividend growth. Therefore, the variation of dividend yields must be due to changing forecasts of expected returns. As argued by Campbell and Thompson (2005), these results are consistent with the view of value-oriented investors to whom high valuation ratios point to an undervalued stock market and predict high subsequent returns. However, empirical evidence supporting this view is weak as well. On the one hand, traditional valuation ratios are shown to forecast stock price changes poorly in the short run (Campbell and Shiller, 1998; Rapach and Wohar, 2006a). On the other hand, several studies have cast doubt on their long-term predictive ability. For instance, Valkanov (2003), Torous, Valkanov, and Yan (2004), and Campbell and Yogo (2006) reexamine the evidence for predictability using tests that have the correct size when the predictor variable is highly persistent: they find that the predictive power of the dividend yield at long-horizons is considerably weakened.[16] Bossaerts and Hillion (1999) and Goyal and Welch (2006) point out that valuation ratios (among other variables) have some in-sample predictability but exhibit weak to no out-of-sample predictive power, be it in the short or long run.

The poor linear predictive power of TVR found in recent empirical studies should in fact come as no surprise. Because of their high level of persistence, valuation ratios can move far outside their historical range. This poses a challenge both to the traditional view that stock prices reflect rational expectations of future cash flows, and to the 'Campbell and Shiller' view

[16]Once uncertainty around the integration order of the valuation ratio is accounted for, Torous, Valkanov, and Yan (2004) find reliable in-sample evidence of predictability at shorter rather than at longer horizons. However, this holds only in the post-1952 subsample and no out-of-sample analysis is carried out.

that TVR are substantially driven by mean reversion. Lack of mean-reversion would suggest also that prices and dividends (or earnings) randomly drift apart in the long run or, equivalently, that they do not cointegrate. Even when TVR cointegrate, they adjust very slowly, casting doubt on their ability to forecast stock price changes. All in all, linear model specifications of TVR lead to the counterintuitive finding that stock price deviations from fundamentals are long lasting, even permanent.

Given the near persistence and the resulting poor predictive ability of TVR, the BEYR has gained the interest of market practitioners. However, there is no comprehensive, in-sample and out-of-sample, statistical assessment of the fundamental cointegration dynamics implied by the BEYR. Most importantly, the reversion dynamics in the BEYR, possibly revealed by the in-sample estimation of the cointegration model, may not be powerful enough to reject the hypothesis that the BEYR does not fundamentally differ from a random walk in the short run. If the cointegration model cannot forecast the BEYR better than the random walk in the out-of-sample application, there is no a priori reason to believe that the BEYR does a good job at forecasting short-term stock returns. We focus on this research agenda in Section 5.

3. The dataset

Our dataset includes the dividend and earnings yields for selected stock indices, the stock price indexes by themselves, as well as the 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. The stock 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.

For each country, we plot the BEYR ratios in Figures I and II. Although the BEYR seems to cross the sample average quite often, it does so at intervals which can go beyond several years, suggesting near persistence and low mean-reversion. As such, the ratios display large up and down swings. 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.[17] 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 than in the early 2000.

Table I shows that the unit root null of the ADF test cannot be rejected for most of the BEYR series. There is ample evidence of near persistence, especially for the BEYR with dividends. Although the failure to reject the null points to a near persistence in the BEYR, it does not necessarily imply the absence of cointegration between the components of the BEYR. As Torous, Valkanov, and Yan (2004) indicate, the order of integration of of slowly mean-reverting processes (such as the BEYR or TVR) is subject to considerable uncertainty.

4. Modelling and forecasting the BEYR

We first use the cointegration methodology à la Johansen to study the reversion dynamics underlying the BEYR. We also model the BEYR using the ARMA-GARCH methodology as it is commonly done for modelling near-persistent processes (Stambaugh, 1999; Lewellen, 2004). We then explain how out-of-sample forecasts of the cointegration and ARMA-GARCH models are generated. Finally, we discuss the equally and superior predictive ability tests used to compare the short-run ability of the aforementioned models in forecasting the BEYR.

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

4.1. The cointegration model

In most papers, there is no prior test for cointegration between the variables involved in the BEYR equation (Shen, 2003; Asness, 2003; Berge and Ziemba, 2006; ap Gwilym, Seaton, Suddason, and Thomas, 2006). 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. In other studies (Campbell and Shiller, 1987; MacDonald and Power, 1995), the cointegration is used, but without the bond yield as input. Although Harasty and Roulet (2000) take the 10-year bond yield as an input, they use the 2-step Engle-Granger methodology. This implies that their cointegrated model is reduced to a single equation and that there are no statistical tests on the coefficients of the long-term relationship. In this paper, 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.[18] 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. Six unit root tests have been used to overcome the potential problems 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 thus 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. As a robustness check, we also consider the Dickey and Pantula (1987) approach to determine the order of integration of the variables.

The second step requires Johansen's cointegration tests. The number of lags (k^*) in the multivariate model is determined such that the last included $k^* + 1$ lagged variables in the VAR specification are jointly non significant. Moreover, we compute the usual univariate and

[18] Durré and Giot (2006) follow the same methodology in their analysis of the Fed model, but they do not investigate the specification with dividends.

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.

Because the d_t, e_t and p_t series exhibit a positive drift, 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).

Johansen (1992) suggests the use of the Pantula principle to test the joint hypothesis of the rank order and the deterministic components. We define c as the rank of the long-run coefficient matrix and n as the number of variables included in the cointegration analysis. 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). 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 when the null hypothesis is not rejected.

When the null of no cointegration is rejected, we estimate the ECM-VAR model to assess the short-run and long-term dynamics of the system. Let us illustrate with the earnings as inputs. If there is one cointegration relationship between the three variables and if the constant is unrestricted, the VAR-ECM is:

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

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

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

Note that this is Model 3 as we do not constrain the constant to be in the cointegration 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.[19] Let us look at the sign of α_p in Equation (3).[20] Economic good sense suggests a positive α_p if β_p is negative: if stock prices increase (decrease) more than warranted by the increase (fall) in earnings, there is a negative (positive) disequilibrium in the cointegration vector. That is, $e_{t-1} + \beta_p p_{t-1} + \beta_r r_{t-1}$ becomes negative (positive). The system should 'correct' by having stock prices decrease (increase), requiring α_p to be positive. Nevertheless, a positive α_p will only be obtained if the mean-reversion dynamics operating through the stock index variable over the next month is sufficiently strong to respond to long-run disequilibrium effects. For instance, if α_p was equal to zero, the reversion dynamics of p_t would be solely governed by short-run effects at the monthly interval.

In summary, we study the validity of the BEYR approach by testing three hypotheses: There is a cointegration relationship between earnings (or dividends), stock prices and government bond yields (H1); The long-term government bond yield plays a significant role in the long-term relationship (H2); A deviation from the long-run equilibrium impacts stock prices such that the BEYR reverts to its long-run equilibrium (H3).

4.2. ARMA-GARCH type models

Besides the random walk (RW) used as the fundamental benchmark, we also consider a number of popular univariate models: 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.[21] We do not detail these models since they have been widely popularized over the last 15 years and are now 'textbook' econometrics.[22]

[19]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.

[20]The importance of the α_p coefficient is stressed by Lamont (1998) and Campbell and Shiller (2001) in their analysis of TVR. They argue that prices rather than fundamentals (dividends or earnings) do most of the adjustment in bringing the ratios back towards their *long-run* equilibrium levels.

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

[22]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).

4.3. Out-of-sample forecasts of the BEYR and statistical evaluation

We use the following rolling scheme to generate the out-of-sample forecasts. We first divide the total sample of T observations into in-sample and out-of-sample portions, where the in-sample portion spans the first R observations and the out-of-sample portion spans the last P observations.[23]

The first OOS forecast of the cointegration model is generated in the following manner. Estimate the cointegration model given in equations (2) to (4) using data available through period R. Using the parameter estimates as well as e_R, p_R, and r_R, construct a forecast for Δe_{R+1}, Δp_{R+1}, and Δr_{R+1}. Construct the forecast of the BEYR with earnings for period $R+1$ as: $\hat{beyr}_{R+1} = (r_R + \Delta\hat{r}_{R+1}) - (e_R + \Delta\hat{e}_{R+1}) + (p_R + \Delta\hat{p}_{R+1})$. Denote the forecast error by $u_{R+1} = beyr_{R+1} - \hat{beyr}_{R+1}$. The first OOS forecast of ARMA-GARCH models is generated in the usual way (see Brooks, 2002).

In order to generate a second set of forecasts, we update the above procedure one period by using all data available through period $1+R$, excluding the first observation. We repeat this process through the end of the available sample, leaving us with $T-R-1$, or $P-1$, rolling forecast errors for each model.

The rolling BEYR forecasts are first assessed using traditional criteria: Mean Squared Error (MSE), Root Mean Squared Error (RMSE), Median Squared Error (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.

[23] In the empirical analysis, we divide the total sample into two equal in-sample and out-of sample portions.

To formally measure the forecasting accuracy of a model against the random walk, we first use the modified Diebold and Mariano (MDM) test.[24] 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 (i.e. the random walk) 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.[25]

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 (i.e. the random walk) 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 correlation (Lehmann, 1998).[26]

We finally test whether each particular forecasting model is outperformed by the other alternative models using Hansen's (2005) 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.[27] A low P-value indicates that the model is inferior to one or more of the competing

[24]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.

[25]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,

$$L = floor[(\frac{4T}{100})exp(2/9)], \tag{5}$$

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.

[26]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.

[27]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.

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.[28]

5. Empirical results

5.1. Cointegration analysis

The cointegration approach models the BEYR constituents in a truly multivariate framework. It poses the following questions: Are the earnings, dividend and stock indexes integrated of order one? Is the long-term government bond yield also integrated of order one? Are the BEYR constituents 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.

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

[28]The implementation is based on the stationary bootstrap but the block bootstrap can also be adopted.

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 the 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) are $I(1)$.[29]

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 three information criteria point $k^* = 2$ as the the optimal lag length in both models (with earnings and dividends). In Japan, the optimal lag length is either $k^* = 2$ or $k^* = 4$ in both specifications (depending on the criteria). 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

[29] 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, cointegration appears to be strong in the VAR system with dividends. Assuming Model 3 is correct, we clearly identify more than one cointegration vector. The Pantula principle indicates 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

There is evidence of cointegration in four countries out of six (H1). The cointegration results given in Table VI show that there exists a long-run stable equilibrium between dividends (earnings), stock prices and bond yields in four (three) countries. When the coefficients on the long-run relationship are significantly different from zero, they show the expected signs in all cases.

The bond yield might play a statistically significant role in the long-term relationship (H2), but results are not conclusive. First, the choice of the estimation sample matters. While the bond yield is relevant over the 1975 - 2000 period, it does not seem to be the case over the 1973 - 2004 period. Second, the choice of the BEYR specification matters too. The bond yield appears to be more relevant in the BEYR specification with dividends. All in all, it is difficult to determine whether the BEYR contains more information than the price-earnings (or price-dividends) ratio at the monthly horizon.[30] Note of course that the bond yield still enters the system through the short-term dynamics, even if it is not statistically relevant in the long-run equilibrium relationship.

[30] Interestingly, in their analysis of the Fed model, Durré and Giot (2006) show that the economic significance of the bond yield is very small.

There is overall mixed evidence of monthly reversion dynamics towards the long-term equilibrium (H3). On the positive side, when the adjustment speed coefficients are significantly different from zero, they all show the expected signs. Moreover, as expected, the reversion dynamics of stock prices drives most of the adjustment process towards the long-run equilibrium. For example, over the period 1973-2004, the US is characterized by $\alpha_p = 0.05$ and $\beta_p = -0.76$. Although we do not have $\beta_p = 1$, the combination of a negative β_p and positive α_p indicates that high stock prices with respect to earnings do lead to poor future stock market performance. On the negative side, α_p is not always significant and the small absolute values of the adjustment speed coefficients point to a slow dynamical reversion process at the monthly horizon.[31] This implies that equity and bond yields might depart from their long-term relationship for an extended period of time before the reversion process finally bring them back to equilibrium. This is also consistent with the pronounced peaks and troughs of the BEYR (see Figures I to II) and the subsequent stock price adjustments.

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 (Shen, 2003; Asness, 2003; Berge and Ziemba, 2006; ap Gwilym, Seaton, Suddason, and Thomas, 2006). Secondly, we investigate whether the p and r variables are weakly exogenous to the system.[32] As the loadings on p and r are jointly significantly different from zero, there is some statistical evidence of short-term reversion towards the long-run equilibrium in all countries but Germany. Nevertheless, the magnitude of reversion at the monthly interval remains small.

5.2. Statistical evaluation of out-of-sample forecasts of the BEYR

The estimation of the cointegration model reveals mixed evidence of monthly reversion dynamics in the BEYR. At this stage, the fundamental question is to know wether such evidence

[31] An impulse response analysis, not reported but available on request, confirms that shocks do not die away quickly and that a given variable needs several years to reach its new long term value.

[32] 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.

is significant enough to reject the idea that the BEYR does not fundamentally differ from a random walk in the short run. If the cointegration model cannot generate more accurate out-of-sample forecasts of the BEYR than the random walk, there is a priori no reason to believe that the BEYR is a good predictor of monthly stock returns.

A quick inspection of the results in Tables VIII to XI reveals that it is challenging to deliver relevant out-of-sample forecasts of 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. 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. The cointegration model is robust in its ability to forecast direction changes in the BEYR. While the null hypothesis 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, 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 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 somewhat 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 Hansen (2005) 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. For the cointegration model however, the null hypothesis of the SPA test is never rejected at the 5% level.

6. Conclusion

Recently, the financial community has turned its attention to an 'augmented' valuation ratio, the Bond-Equity Yield Ratio (BEYR). In contrast to the usual earnings yield or dividend yield ratios, by relying upon both the long-term bond yield and the equity yield, the current BEYR is argued to exhibit enhanced predictive power for forecasting stock returns.

A number of papers use OLS predictive regressions to examine the predictive ability of close variants of the BEYR, but most of them are characterized by serious econometric shortcomings. Some authors advocate the use of enhanced specifications to better model the near persistence of valuation ratios, but then specification search becomes a issue.

This paper takes a different tack to assess the predictive ability of the BEYR. We stick to the original, well-established framework of cointegration that has been used in earlier papers to examine the reversion dynamics displayed by TVR, like the dividend yield or the price-earnings ratio. By using cointegrated VAR (or VECM) models, we indirectly assess the predictive ability of the BEYR.

The in-sample estimation of the cointegration model reveals mixed evidence of reversion dynamics in the BEYR. Based on monthly data, we find no evidence of cointegration for two countries, out of six. As such, there is no reversion dynamics in the BEYR, rejecting the whole idea that the BEYR can be used for predicting stock returns. Second, it is difficult to determine whether the BEYR contains at the monthly horizon more information than the price-earnings or price-dividends ratios. Third, even when the components of the BEYR cointegrate, the reversion dynamics towards the long-term equilibrium are still very slow, casting doubt on the ability of the BEYR to forecast stock price changes. The small absolute values of the adjustment speed coefficients indeed point to a slow dynamical reversion process at the monthly horizon.

The out-of-sample analysis reveals that the slow reversion dynamics of the BEYR towards its long-run equilibrium found in the in-sample cointegration analysis is insufficient to reject the hypothesis that the BEYR follows a random walk at the monthly horizon. As such, both the equal predictive ability (EPA) tests and the Hansen (2005) superior predictive ability (SPA) test cast doubt on the ability of the BEYR to predict monthly stock returns.

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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
ADF (none)	-0.85	-1.06	-0.86	-0.84	-1.21	-0.72
ADF (const)	-2.14	-2.29	-1.20	-2.37	-2.42	-1.71
ADF (trend)	-1.96	-2.28	-1.38	-2.64	-4.40***	-2.20
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
ADF (none)	-1.41	-1.32	-0.92	-0.99	-1.13	-1.09
ADF (const)	-2.59*	-2.46	-1.40	-2.40	-2.98**	-2.66*
ADF (trend)	-2.62	-2.56	-1.78	-2.91	-3.04	-3.17*

ADF denotes the Augmented Dickey-Fuller Test. The optimal lag length is determined by the MAIC as defined by Ng and Perron (2001). The test is carried out with no exogenous variable (none), a constant (const) and both a constant and a trend (trend). 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,$(1\beta_p\beta_r)$, gives the coefficient of each variable in the long-run relationship with the first weight on d (or$e$) 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)
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
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

COINT denotes the cointegration model. For instance, COINT(3,2) denotes the Model 3 of cointegration (with an unrestricted constant and no trend) with 2 lags. RW denotes the Random Walk model. 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
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
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)

COINT denotes the cointegration model. For instance, COINT(3,2) denotes the Model 3 of cointegration (with an unrestricted constant and no trend) with 2 lags. RW denotes the Random Walk model. 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
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)
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

COINT denotes the cointegration model. For instance, COINT(3,2) denotes the Model 3 of cointegration (with an unrestricted constant and no trend) with 2 lags. RW denotes the Random Walk model. 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)
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)

COINT denotes the cointegration model. For instance, COINT(3,2) denotes the Model 3 of cointegration (with an unrestricted constant and no trend) with 2 lags. RW denotes the Random Walk model. 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.

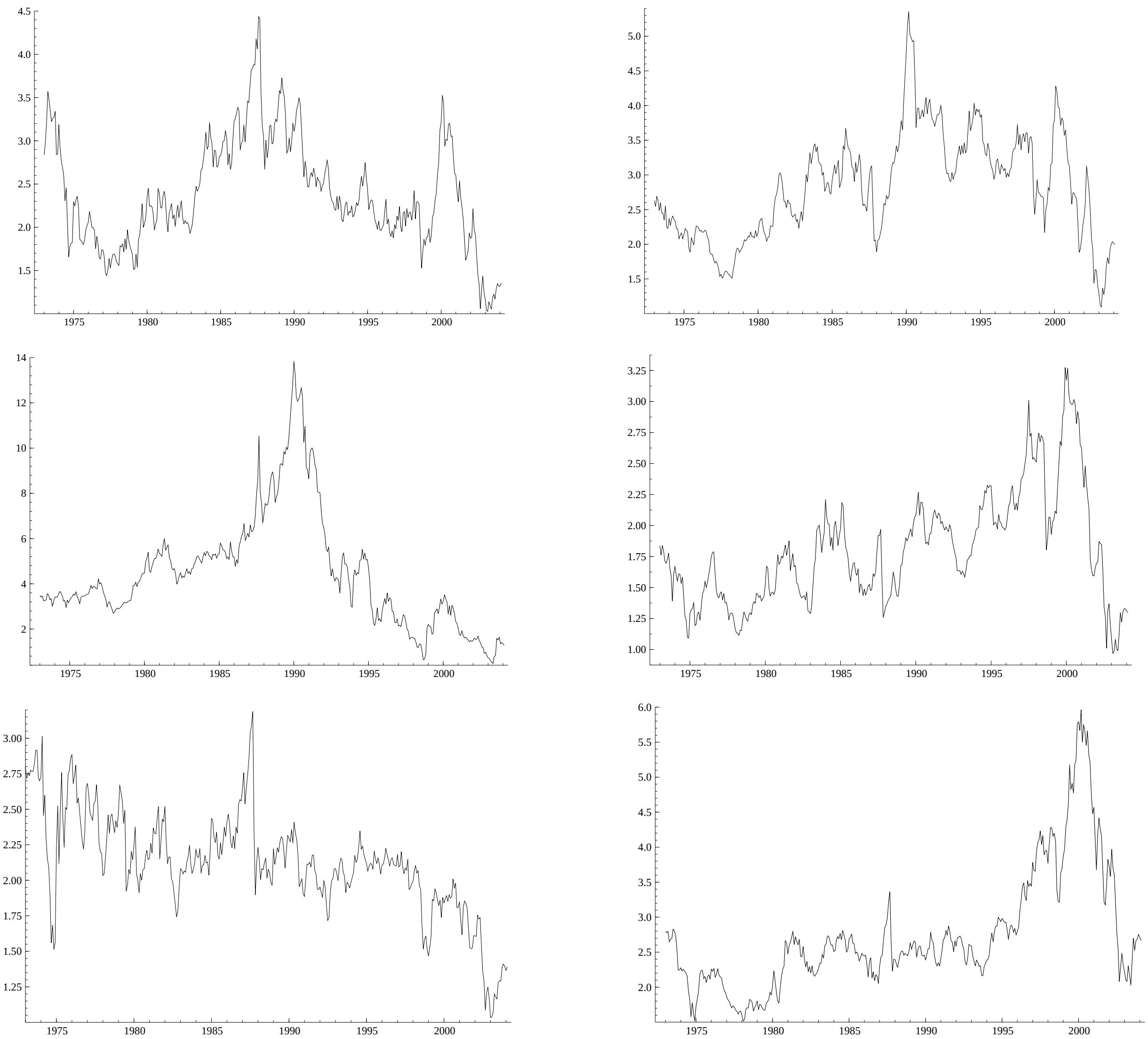

Figure I. The Bond-Dividend Yield Ratio. From top left to bottom right: France, Germany, Japan, the Netherlands, the UK, and the US.

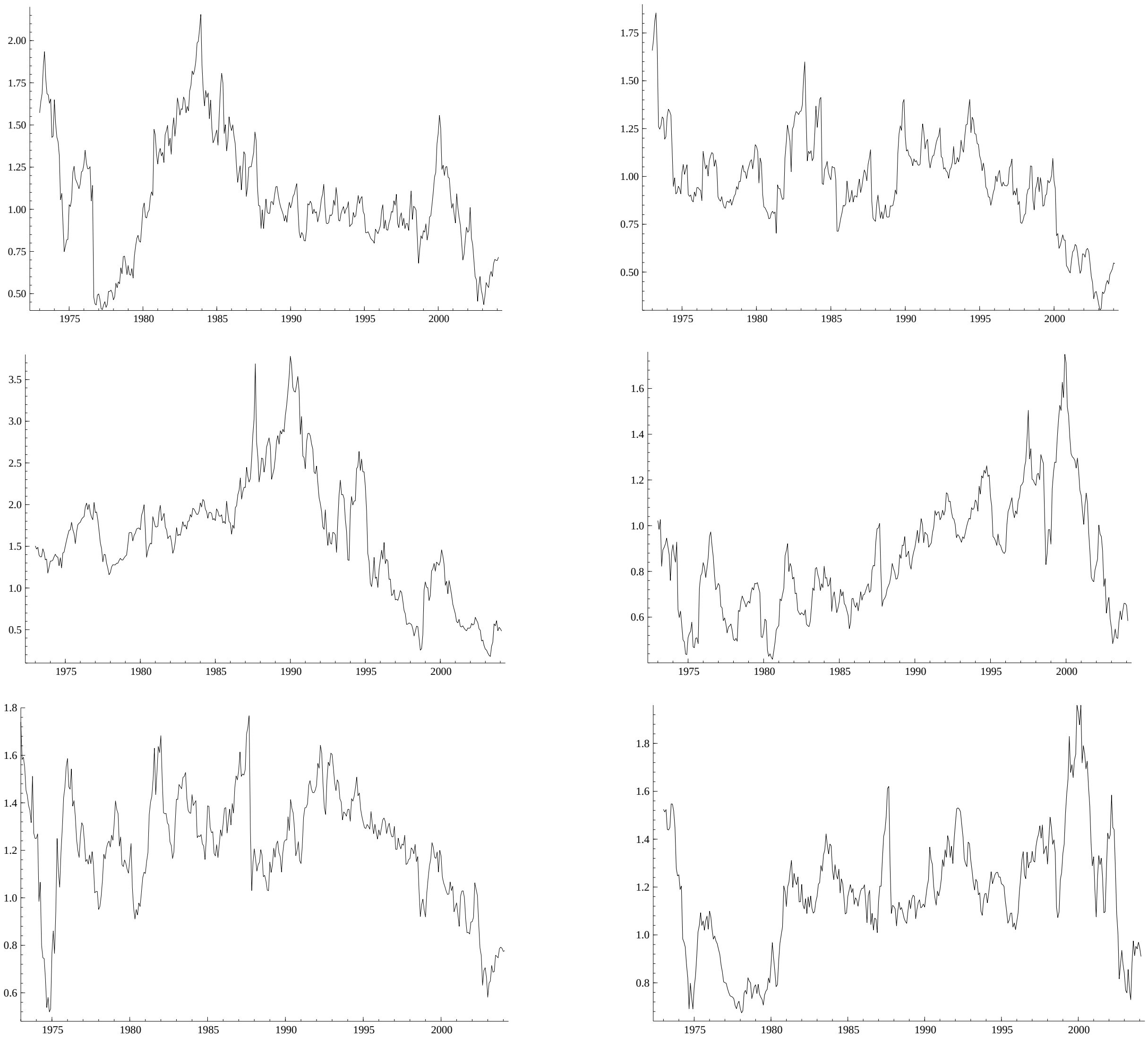

Figure II. The Bond-Earnings Yield Ratio. From top left to bottom right: France, Germany, Japan, the Netherlands, the UK, and the US.