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CAN DIVIDEND YIELDS OUT-PREDICT UK STOCK RETURNS WITHOUT SHORT RATES?*

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Can dividend yields out-predict stock returns without short rates? Using monthly data of the UK over the period of 1923–2007, in this paper we investigate both in- and out-of-sample predictability of stock returns based on dividend yields. Empirical results indicate that the predictability of UK's stock returns is visible without short rates if the forecast horizon is greater than four months. The above finding is new in literature and results from adopting a long data set and a non-linear modeling strategy.

1 Introduction

Since the seminal papers by Campbell and Shiller (1988) and Fama and French (1988), a central research topic in empirical financial economics over the past 30 years has been the predictability of stock returns.[1] Most literature related to return predictability has relied on a long-horizon regression equation with dividend yields or price-earning ratios as a regressor. The 'conventional wisdom' in literature is that valuation ratios predict stock returns, and the predictability is stronger for longer horizons (Campbell, 1991; Cochrane, 1992; Campbell *et al*., 1997).

Small sample bias and serial correlation in residuals are two well-known technical problems inherent in long-horizon regressions. Considering these two problems, the evidence of return predictability becomes weaker (Goetzmann and Jorion, 1993; Nelson and Kim, 1993; Ang and Bekaert, 2007). Robertson and Wright (2006) argue that the reason could be due to a mismeasurement of valuation ratios, and their study finds in-sample evidence of long-horizon return predictability after constructing a new cash-flow yield.

Although stock returns are in-sample predictable at long horizons, many articles have found that out-of-sample predictability is much weaker (Goyal and Welch, 2003; Lettau and Van Nieuwerburgh, 2008). Rapach *et al*. (2005)

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[1]Campbell and Shiller (1988) find that valuation ratios, such as dividend yields, on aggregate stock portfolios predict expected stock returns when forecast horizons are long.

find evidence of out-of-sample return predictability in short horizons if short-term interest rates are included. Several authors also emphasize the significance of modeling financial variables with a non-linear framework (Rapach and Wohar, 2005; Coakley and Fuertes, 2006; Paye and Timmermann, 2006; McMillan, 2007; Lettau and Van Nieuwerburgh, 2008). Whether non-linear modeling strategy allows for out-predicting UK stock returns at short horizons without short rates is an interesting topic. This paper applies an exponential smooth transition autoregressive model to describe the dynamics of dividend yields and then examine if a conventional return prediction equation beats random walks in out-of-sample contests.

Applying UK's monthly data over the period of 1923–2007, empirical results show that the predictability of UK's stock returns is visible without short rates if the forecast horizon is greater than four months. The simulation analysis of this paper points out that bootstrap tests have the correct size and achieve a reasonably high power and the main results of this paper are not affected significantly if an alternative moving block bootstrap is applied. Rapach *et al.* (2005) and Ang and Bekaert (2007) find evidence of return predictability in short horizons if short-term interest rates are included. Results of this paper contrast with the above two papers and two reasons are responsible for these differences. First, the modeling strategy of this study is notably non-linear instead of linear. Second, the sample period is much longer than that of existing literature, increasing the number of observations in out-of-sample contests and hence the power of out-of-sample statistics.

This paper is organized as follows. Section 2 describes the empirical methodology. Section 3 provides the results of return predictability based upon in- and out-of-sample tests. Section 4 investigates powers and sizes of bootstrap tests based on a residual bootstrap. It also examines if our findings based on residual bootstrap are robust to an alternative moving block bootstrap provided by Künsch (1989). Finally, Section 5 summarizes major conclusions.

2 Empirical Methodology

Existing literature typically uses the long-horizon predictive regression model to examine the predictability of stock prices indicated below:

$$r_{k,t}^{j} = \alpha_k^j + \beta_k^j w_t + \varepsilon_{t+k}^j \qquad k = 1, 3, 4, 6, 9, 12, 24, 36, 48, 60 \qquad j = 1, 2 \qquad (1)$$

where, $r_{k,t}^{j}$ is the jth, k horizon real stock return between t and $t+k$, and w_t is the dividend yield in log-levels constructed as the deviation of real dividend in log-levels from the real stock price in log-levels (p_t), hence $w_t = d_t - p_t$. This paper investigates two different returns: aggregate and excess returns. The aggregate return ($r_{k,t}^{1}$) includes both dividends and capital gains, and the excess return ($r_{k,t}^{2}$) is constructed by subtracting a risk-free interest rate (r_t^f) from the aggregate return. Let $r_{1,t}^{1} \equiv \log[(P_{t+1} + D_{t+1})/P_t]$ and $r_{1,t}^{2} = r_{1,t}^{1} - r_t^f$ where

P_t and D_t are the real stock price and dividend payout, respectively, then the stock return with a horizon k is $r^j_{k,t} \equiv \sum_{i=1}^{k} r^j_{1,t+i-1}$ for $j = 1, 2$ and $k = 1, 2, \ldots$.

The theoretical justification of equation (1) derives from the implication of Gordon's (1962) growth model which states that the long-run equilibrium dividend yield is a constant determined by the mean real discount rate and the mean growth rate of real dividends.[2] If real stock prices are low relative to real dividends, then investors expect stock prices to eventually adjust to restore the long-run equilibrium between stock prices and fundamental values. Therefore, a stable dividend yield provides an apparently plausible explanation for stock return predictability.

Based on equation (1), the non-predictability of stock returns can be examined by testing the hypothesis of $\beta_k = 0$ versus $\beta_k > 0$ for a given forecast horizon of k. The estimate of β_k is subject to the problem of finite-sample bias since the innovations of dividend yields and returns may be correlated (Keim and Stambaugh, 1986). Therefore, the t statistic of β_k, $t(k)$, does not have the conventional distribution. This work constructs the finite-sample distribution of t statistics and a joint statistic $t_{\max}$ ($\max\{t(k)$: $k = 1, 3, 4, 6, 9, 12, 24, 36, 48, 60\}$) through a residual bootstrap described in Appendix A.

The current study examines out-of-sample return predictability by testing the hypothesis of equal accuracy of forecast errors from equation (1) and a random walk benchmark. Conventionally, researchers apply t- and F-type Diebold–Mariano statistics, provided by Diebold and Mariano (1995) and Clark and McCracken (2001, 2004), to examine the null hypothesis of equal accuracy of forecasts when the two models are nested. The above Diebold–Mariano statistics use the mean square prediction error to test the hypothesis of no-predictability of stock returns. Clark and West (2006, 2007) point out that under the null hypothesis of no predictive ability, the mean square prediction error of the null model should be smaller than that of the alternative model. They therefore suggest using the mean square prediction error-adjusted series to test the non-predictability hypothesis, denoted as the CW test. The limiting distribution of the CW statistic and the joint statistic $\mathrm{CW}_{\max}$ ($\max\{\mathrm{CW}(k)$: $k = 1, 3, 4, 6, 9, 12, 24, 36, 48, 60\}$) is not standard, and hence its finite-sample distribution is simulated through the bootstrap.[3]

Conventional literature assumes that dividend yields follow a linear autoregressive process. Rapach and Wohar (2005) point out that the pattern

[2]The basic stock price valuation model points out that the current stock price is equal to the present values of the next period's expected stock price and dividend: $P_t = E_t[p_{t+1} + D_{t+1})/(1 + \rho_{t+1})]$, where ρ_{t+1} is the real discount rate. After assuming that both the real discount rate and real dividend growth are constant, and that there is no bubble solution, we solve the above equation for the stock price by forward induction. The resulting long-run equilibrium dividend yield (w^*) is a function of mean real discount rate (ρ) and the mean growth of real dividends (g): $w^* = \log[(\rho - g)/(1 + g)]$.

[3]The bootstrap procedures are similar to those described in Appendix A. The only difference is that we construct the CW statistic in the third step.

of return predictability will be consistent with that of power if assuming non-linear dynamics of dividend yields. This work therefore assumes that dividend yields follow a second-order, non-linear exponential smooth transition autoregressive (ESTAR(2)) model given as follows:[4]

$$w_t = b + [\alpha * (w_{t-1} - b) + (1-\alpha) * (w_{t-2} - b)] * F[w_{t-1}, \theta, b] + u_t$$

$$F[w_{t-1}, \theta, b] = \exp\left[\theta (w_{t-1} - b)^2\right] \qquad u_t \sim \text{i.i.d.}(0, \sigma^2) \qquad \theta < 0 \tag{2}$$

where $F[w_{t-1}, \theta, b]$ is a transition function bounded between zero and one. In the case where the deviation of the dividend yield from its long-run equilibrium (b) is small, the value of F is close to one, and the dividend yield is highly persistent. Otherwise, it is stationary.

Financial markets may be characterized by non-linear behavior resulting from market friction and transaction costs (Dumas, 1992; Sercu *et al.*, 1995), and the interaction between heterogeneous traders (Poterba and Summers, 1986; Shleifer and Summers, 1990; Gallagher and Taylor, 2001). Given the actions of noise traders, the perceived deviations of asset prices from their fundamental value represent risky arbitrage opportunities. Arbitrage in stock markets will be observed only when perceived price deviations are large, since small price deviations imply that the perceived gains may be too small to outweigh this risk. The above risk arbitrage hypothesis implies non-linear dynamics of asset prices.

3 Empirical Investigation

3.1 Data Description

This study obtains monthly data for the consumer price index, stock prices and dividends for the UK over the period of 1923–2007 from Global Financial Data. Dividend yields are constructed by dividing the dividend through the stock price. The UK stock price is the real Financial Times Stock Exchange all-share price index. The consumer price index is used to convert the series of nominal stock prices into real terms. The current empirical analysis applies two different definitions of stock returns. The aggregate return ($r^1_{k,t}$) includes both capital gains and dividends, and the alternative is the excess return ($r^2_{k,t}$) defined as the aggregate return minus a risk-free interest rate, measured by the three-month treasury-bill rate.

[4]One may argue that a threshold-type model is appropriate for modeling the non-linear dynamics of the dividend yield (Coakley and Fuertes, 2006). In fact, different agents might have different transaction costs, suggesting that thresholds might become blurred as one aggregates the model over different agents. In other words, non-synchronous adjustment of heterogeneous agents and time aggregation are likely to result in smooth aggregate regime switching. Therefore, a smooth transition autoregressive model seems a more attractive option than a threshold autoregressive model in describing the non-linear adjustment of the dividend yield.

Table 1
Unit-Root Tests of Dividend Yields

ADF	*ERS*	MZ_{α}	MZ_t	*MSB*	*MPT*
–3.098*	–2.784*	–17.764*	–2.808*	0.158*	2.010*

Notes: ADF is the augmented Dicky–Fuller statistic. ERS is the unit-root statistic provided by Elliott *et al.* (1996). MZ_{α}, MZ_t, MSB and MPT are statistics provided by Ng and Perron (2001). The lag order of the model is determined based on modified Akaike information criterion. The term '*' indicates significance at the 5 per cent level.

3.2 *The Stationarity of Dividend Yields*

Dividend yields in equation (1) must be stationary, otherwise predicting returns with a non-stationary regressor is meaningless (Lanne, 2002). Empirical literature widely uses conventional augmented Dicky–Fuller (ADF) tests to examine the stationarity of variables. However, the power of ADF tests is low when the root is close to one, and the tests are very sensitive to model misspecification (Schwert, 1987). Elliott *et al.* (1996, hereafter ERS) and Ng and Perron (2001, hereafter NP) develop unit-root tests, based on generalized least square de-trended data, with better size and power properties than conventional ADF tests. This work therefore applies the ADF, ERS and NP tests to examine the stationarity of dividend yields and reports results in Table 1. The model adopted in unit-root tests is the one with a constant and the model's lag length is determined based on the modified Akaike information criterion. Results from Table 1 indicate that all statistics consistently reject the unit-root hypothesis at conventional levels of significance. The above results are interesting since several articles support the unit-root hypothesis of the price–dividend ratio and hence reject the present value model (Froot and Obstfeld, 1991; Lamont, 1998). The reason could be due to the fact that the sample period in this paper covers almost a century that significantly raises the power of unit-root tests. Rejecting the unit-root hypothesis of dividend yields is important since it points out that the dividend yield is a legitimate variable in predicting returns.

3.3 *Return Predictability with Non-linear Dynamics of Dividend Yields*

Several articles indicate the non-linear dynamics of financial variables, rendering the bias inference of test statistics if such behavior is not taken into account.[5] The current study examines if non-linearities of dividend yields in the UK's stock markets are significant.

Results from Table 2 point out that parameters in equation (2) are all significant at the 5 per cent level of significance. The test statistic (t_{θ}) for the

[5]The finite-sample distribution of t and CW statistics under a linear data-generating process (DGP) will be different from that under a non-linear DGP. This leads to bias inferences of tests if there are significant non-linearities in dividend yields but empirical analysis neglects these non-linearities.

TABLE 2
MODEL ESTIMATES

$w_t = b + \{\exp[\theta^*(w_{t-1} - b)^2]\}^*[\alpha^*(w_{t-1} - b) + (1 - \alpha)^*(w_{t-2} - b)] + \varepsilon_t$

b	θ	α	*Q(8)*	*Q(12)*	*ET*	*RESET(1)*	*RESET(2)*
−3.20	−0.086	1.205	8.332	19.280	0.481	0.493	0.318
(<0.001)	(<0.001)	(0.001)	(0.402)	(0.082)	(0.488)	(0.483)	(0.728)

Notes: The number in a parenthesis is a p value. '<0.001' in a parenthesis indicates the p value is less than 0.001. $Q(p)$ is the Ljung–Box autocorrelation tests for up to a pth-order autocorrelation having a χ^2 distributions with p degrees of freedom. ET is the statistic provided by Eitrheim and Teräsvirta (1996) testing for any remaining autocorrelation in the residuals of a non-linear regression model. RESET is the Ramsey's regression specification error test that has an F distribution. The p values for the estimated transition parameter, θ, is constructed based on a non-parametric bootstrap.

hypothesis that θ equals zero does not have a conventional distribution as pointed out by Taylor and Peel (2000), and hence the empirical distribution of t_θ is simulated through the bootstrap. Q statistics reveal no evidence of serial correlation in estimated residuals. The test by Eitrheim and Teräsvirta (1996) indicates no evidence of any remaining autocorrelation in the residuals of a non-linear regression model. Finally, Ramsey's regression specification error test (RESET) indicates no evidence of model misspecification at conventional levels. Finding non-linear dynamics of dividend yields supports the significance of noise trading on asset price dynamics (Poterba and Summers, 1986; Shleifer and Summers, 1990; Gallagher and Taylor, 2001)

Table 3 reports forecast contests for the horizon of one, three, four, six, nine months and one to five years under the assumption of non-linear dynamics of dividend yields in equation (2).[6] The significance of β_k in equation (1) reveals evidence of in-sample return predictability, and this work simulates critical values of $t(k)$ and $t_{\max}$ through a residual bootstrap to conduct the inference of β_k. Results from rows three and six of Table 3 reject the hypothesis of no return predictability at the 5 per cent level for both returns when the forecast horizon is greater than one month. In addition, the joint statistic $t_{\max}$ also rejects the hypothesis. In short, empirical results reveal that the predictive ability of dividend yields is visible at both short and long horizons. Results from Table 3 contrast with those from Ang and Bekaert (2007) which found that excess return predictability is not statistically significant at long horizons.

To evaluate the out-of-sample predictability of stock returns, this paper estimates the long-horizon predictive equation in (1) and then compares the sequence of forecast errors from equation (1) with those from a random walk with drift: $r_{1,t}^j = \alpha_1^j + \varepsilon_{t+1}^j$ where ε_{t+1}^j is an independent and identically distributed disturbance. This study reserves the first 30-year observations for estimation and hence the out-of-sample forecast period starts from 1953. We

[6]Following Rapach and Wohar (2005), we simulate the finite-sample distribution of t and CW statistics through the bootstrap.

TABLE 3
RESIDUAL BOOTSTRAPPED *p* VALUES

	1 month	*3 months*	*4 months*	*6 months*	*9 months*	*12 months*	*24 months*	*36 months*	*48 months*	*60 months*	*JS*
Aggregate returns, $r^1_{k,t}$											
$t(k)$	0.188	**0.040**	**0.041**	**0.031**	**0.020**	**0.015**	**0.010**	**0.002**	**0.001**	**0.002**	**0.002**
CW(k)	0.390	0.150	**0.077**	**0.050**	**0.048**	**0.039**	**0.036**	**0.026**	**0.025**	**0.019**	**0.032**
Excess returns, $r^2_{k,t}$											
$t(k)$	0.252	**0.048**	**0.038**	**0.040**	**0.026**	**0.024**	**0.020**	**0.006**	**0.002**	**0.008**	**0.008**
CW(k)	0.506	0.224	0.120	**0.058**	**0.052**	**0.042**	**0.042**	**0.036**	**0.028**	**0.034**	**0.048**

Notes: CW(k) indicates the statistic provided by Clark and West (2007) where k is the forecast horizon. JS indicates a joint statistic. $r^1_{k,t}$ and $r^2_{k,t}$ are aggregate returns and excess returns, respectively. Boldface values indicate significance at the 10 per cent level.

re-estimated the long horizon predictive equation each time after adding one observation to the sample and thus used only data available up to the forecast date.

This paper applies the CW(k) statistic provided by Clark and West (2006, 2007) to examine the out-of-sample predictability of stock returns at the kth forecast horizon and examines whether forecast errors from the long-horizon predictive equation are significantly smaller than those from the benchmark random walk model. The Newey–West method is applied to construct an autocorrelation consistent standard error. The truncated lag in constructing the Newey–West covariance matrix is determined based on Andrew's (1991) procedure. A joint test is also applied to examine whether the largest CW statistic, $\mathrm{CW}_{\max}$, among the 10 horizons is significant. The finite-sample distribution of CW statistics is simulated through the residual bootstrap based on the data-generating process (DGP) of equation (3). Results from rows four and seven of Table 3 indicate that the CW statistic is significant at the 10 per cent level when the forecast horizon is greater than three months for aggregate returns and four months for excess returns. The $\mathrm{CW}_{\max}$ statistic is significant for both returns.

How robust are the results from Table 3 to the assumption of non-linear regressors and the residual-bootstrapped method? In response, this paper adopts a block bootstrap which does not require specific assumptions on the DGP of regressors. To be specific, this work applies the moving block bootstrap to resample the pairs of observations $x_t^j = \left(r_{k,t}^j, w_t\right)'$ and then re-examines the p values of bootstrap tests (Künsch, 1989; Liu and Singh, 1992).[7] The reason for using the block bootstrap is because of the existence of a serial correlation in both dependent and independent variables. An advantage of using the block bootstrap is that it does not depend on the specific non-linear model in equation (2) and allows for a more general form of non-linearity in dividend yields. In addition, the block bootstrap is valid even in the presence of conditional heteroskedasticity whereas the previous residual-based bootstrap is not.[8]

It is worth noting that $r_{k,t}^j$ in equation (1) is serially correlated and the degree of serial correlation increases with forecast horizons. The current research therefore adopts overlapping blocks with the block size increasing with forecast horizons.[9] Results from Table 4 indicate that the hypothesis of no return predictability is rejected at conventional levels by t and CW

[7]To be specific the block size is set to 1, 3, 4, 6, 9, 12, 24, 36, 40 and 40 for the horizon of 1, 3, 4, 6, 9, 12, 36, 48 and 60 months, respectively. Notice that when the block size is one, the block bootstrap here is the same as pairwise bootstraps originally proposed by Freedman (1981) (Davidson and MacKinnon, 2004).

[8]We appreciate a referee suggesting this alternative bootstrap method to us, and detailed procedures of the block bootstrap are described in Appendix C.

[9]Simulation results by Goncalves and Vogelsang (2008) point out that increasing the block size helps to reduce the size distortion of the block bootstrap if the strength of the serial correlations increases.

Table 4
Block Bootstrapped *p* Values

	1 month	*3 months*	*4 months*	*6 months*	*9 months*	*12 months*	*24 months*	*36 months*	*48 months*	*60 months*	*JS*
Aggregate returns, $r^1_{k,t}$											
$t(k)$	0.108	**0.015**	**0.011**	**0.015**	**0.008**	**0.008**	**0.001**	**0.001**	**0.000**	**0.000**	**0.001**
CW(k)	0.668	0.346	0.178	**0.073**	**0.043**	**0.029**	**0.020**	**0.006**	**0.002**	**0.002**	**0.033**
Excess returns, $r^2_{k,t}$											
$t(k)$	0.139	**0.019**	**0.018**	**0.019**	**0.009**	**0.011**	**0.004**	**0.001**	**0.000**	**0.000**	**0.001**
CW(k)	0.897	0.439	0.256	**0.100**	**0.065**	**0.035**	**0.035**	**0.011**	**0.004**	**0.010**	0.102

Notes: CW(k) indicates the statistic provided by Clark and West (2007) where k is the forecast horizon. JS indicates a joint statistic. $r^1_{k,t}$ and $r^2_{k,t}$ are aggregate returns and excess returns, respectively. Boldface values indicate significance at the 10 per cent level.

statistics when the forecast horizon is greater than one and four months, respectively. Based on the block bootstrap, this paper finds that dividend yields are helpful in predicting the UK's aggregate and excess returns when the forecast horizon is greater than four months. The CW_{max} statistic is significant for aggregate returns but is insignificant, with a *p* value of 0.102, for excess returns. These results are similar to those founded in Table 3.

Künsch (1989) points out that the block bootstrap distribution and the true distribution are in good agreement for linear statistics. However, if the statistic is a non-linear transformation of a linear statistic, such as t_{max} and CW_{max}, having distribution not close to normal, the block bootstrap reflects the non-normality of the distribution only to some extent.[10] Therefore, it may not be appropriate to examine the hypothesis of no return predictability based on t_{max} and CW_{max} statistics unless the sizes of these statistics are known.

Table 3 reveals two interesting results. First, results from out-of-sample tests are similar to those from in-sample tests. Inoue and Kilian (2004) and Rapach and Wohar (2006) show that, if appropriate tests are used, in-sample and out-of-sample tests are equally reliable, and hence should have similar results. Second, the predictability of UK's stock returns is visible without short rates if the forecast horizon is greater than four months. This result is interesting since the literature did not observe short-term out-predictability of UK stock returns.

Rapach *et al.* (2005) point out that the evidence of return predictability based on financial ratios is weak and hence re-examine the predictability of price returns by adding several macro-variables to their predictive equation.[11] Based on monthly data, Rapach *et al.* (2005) find that the government bond yield is helpful to predict UK stock returns when the forecast horizon is short (one month). Focusing on excess returns, Ang and Bekaert (2007) find that the in-sample predictive ability of dividend yields is best revealed at short forecast horizons with a short rate as an additional regressor, consistent with that of Rapach *et al.* (2005). Ang and Bekaert (2007) also point out that excess return predictability is not statistically significant at long horizons, different from that of Campbell (2003).

Results from Table 3 point out that, without the assistance of macro variables, dividend yields are helpful in predicting UK stock returns when the forecast horizon is short (greater than one and four months with *t* and CW statistics, respectively). The above result is in contrast to those of Rapach *et al.* (2005) and Ang and Bekaert (2007). In addition, return predictability increases with forecast horizons, different from that of Ang and Bekaert (2007) but consistent with that of Campbell (2003).

[10]See Table 5 in Künsch (1989).
[11]The price return is defined as the log change of stock prices.

This paper and the above-mentioned papers contain two major differences. First, this work adopts a non-linear instead of a linear framework to investigate UK's stock return predictability. Results from Table 3 indicate that a non-linear modeling strategy is helpful to predict stock returns. Second, the sample period of the paper is much longer than that in existing literature.[12] A long data set increases the number of observations in out-of-sample contests, which increases the power of in- and out-of-sample statistics.

4 Size and Power of Bootstrap Tests

Are results from Table 3 due to the over-rejection of bootstrap tests? To address this question, this study investigates the size and power of bootstrap tests. The size of bootstrap tests is evaluated by imposing the non-predictability hypothesis of stock returns. The DGP of stock returns and dividend yields is given as follows:

$$r_{1,t-1}^{j} = \hat{\alpha}_1^{j} + \tilde{\varepsilon}_{1t}^{j} \qquad j = 1, 2$$

$$w_t = \hat{b} + \left[\hat{\alpha} * \left(w_{t-1} - \hat{b}\right) + (1 - \hat{\alpha}) * \left(w_{t-2} - \hat{b}\right)\right] * F\left[w_{t-1}, \hat{\theta}, \hat{b}\right] + \tilde{\varepsilon}_{2t} \tag{3}$$

The residuals for each equation are bootstrapped from actual regression residuals. Based on Kilian (1999) and Rapach and Wohar (2005), this investigation applies a three-step procedure to evaluate the size of bootstrap tests, described in Appendix B.

Results presented on the Size panel of Table 5 indicate that the effective size of in- and out-of-sample bootstrap tests at different forecast horizons is close to the nominal size of 0.10, which is not sensitive to adopted returns. No significant evidence of over-rejection for the bootstrap tests is apparent, and hence our rejection should be due to the high power of bootstrap tests.

To evaluate the power of bootstrap tests, this paper simulates the series for the dividend fundamental (d_t) and dividend yields, which in turn allows us to construct stock returns. The DGP, similar to the one adopted in Rapach and Wohar (2005), is given as follows:

$$\begin{aligned} \Delta d_t = {} & 0.0016 - 0.2709 * \Delta d_{t-1} - 0.1351 * \Delta d_{t-2} + 0.0935 * \Delta d_{t-4} \\ & - 0.1724 * \Delta p_{t-1} - 0.0818 * \Delta p_{t-2} + \tilde{u}_{1t} \end{aligned}$$

$$\begin{aligned} w_t = {} & -3.20 + \left\{\exp\left[-0.086 * (w_{t-1} + 3.20)^2\right]\right\} * \\ & [1.205 * (w_{t-1} + 3.20) - 0.205 * (w_{t-2} + 3.20)] + \tilde{u}_{2t} \end{aligned} \tag{4}$$

The price series (p_t) can be constructed from the simulated series of dividends and dividend yields since $p_t = d_t - w_t$. Having the simulated series of p_t and d_t, we construct simulated aggregate returns, $\tilde{r}_{k,t}^{1}$. To simulate excess returns, $\tilde{r}_{k,t}^{2}$,

[12]The sample periods in Campbell (2003), Rapach *et al.* (2005) and Ang and Bekaert (2007) are 1970–99, 1979–2000 and 1953–2001, respectively.

Table 5
Size and Power: Residual Bootstraps

	Size				*Power*			
	$r^1_{k,t}$		$r^2_{k,t}$		$r^1_{k,t}$		$r^2_{k,t}$	
k	$t(k)$	CW(k)	$t(k)$	CW(k)	$t(k)$	CW(k)	$t(k)$	CW(k)
1 month	0.108	0.118	**0.090**	**0.088**	0.938	0.834	0.942	0.814
3 months	0.108	0.110	**0.094**	**0.094**	0.998	0.982	0.998	0.974
4 months	0.112	0.114	**0.098**	**0.092**	1.000	0.988	0.998	0.972
6 months	0.114	0.116	**0.094**	**0.088**	1.000	0.990	0.998	0.974
9 months	0.114	0.120	**0.082**	**0.080**	1.000	0.988	0.998	0.972
12 months	0.110	0.126	**0.092**	**0.086**	1.000	0.988	0.996	0.968
24 months	0.114	0.110	**0.090**	**0.094**	0.996	0.990	0.976	0.944
36 months	0.114	0.114	**0.090**	**0.092**	0.994	0.984	0.944	0.902
48 months	0.126	0.124	**0.080**	**0.092**	0.992	0.964	0.920	0.850
60 months	0.122	0.126	**0.082**	**0.090**	0.984	0.946	0.892	0.806
JS	0.116	0.114	**0.076**	**0.096**	0.996	0.988	0.972	0.920

Notes: CW(k) indicates the statistic provided by Clark and West (2007) where k is the forecast horizon. JS indicates a joint statistic. $r^1_{k,t}$ and $r^2_{k,t}$ are aggregate returns and excess returns, respectively. Boldface values indicate significance at the 10 per cent level.

the DGP in equation (4) is augmented by an interest rate process following a stationary second-order autoregressive process. After simulating $\tilde{r}^1_{k,t}$, we then subtract the simulated interest rate from $\tilde{r}^1_{k,t}$ to obtain the simulated excess returns.

Results from the Power panel of Table 5 indicate that the power of the in-sample bootstrap test is high and varies between 0.89 and 1.0, and the power of the out-of-sample bootstrap test varies in the range of 0.81–0.99. No significant difference exists between the powers of in- and out-of-sample bootstrap tests.

To examine the robustness of results in Table 5, this paper examines the size and power of bootstrap tests based on a block bootstrap. Following Goncalves and Vogelsang (2008) and Cameron *et al.* (2008), this paper specifies the DGP for $r^j_{k,t}$ and w_t and then apply the three-step procedure to evaluate the size and power of bootstrap tests based on a direct block bootstrap.[13] The DGP of $r^j_{k,t}$ and w_t are assumed to be the same as those used in residual bootstrap. Under this assumption, we expect that the size and power from block bootstrap should not be as good as those from residual bootstrap since the information of DGP is ignored in block bootstrap.

Table 6 reports the size and power of bootstrap tests based on a direct block bootstrap. Results from the Power panel of Table 6 indicate that the power of bootstrap tests exceeds 0.85, except for joint statistics and the CW statistic in one-month horizon. Results from the Size panel of Table 6 point out that the size of t statistic for aggregate (excess) returns is close to the

[13]Goncalves and Vogelsang (2008) and Cameron *et al.* (2008) provide standard methods to examine the finite-sample properties of block bootstrap.

TABLE 6
SIZE AND POWER: BLOCK BOOTSTRAPS

	Size				*Power*			
	$r^1_{k,t}$		$r^2_{k,t}$		$r^1_{k,t}$		$r^2_{k,t}$	
k	$t(k)$	CW(k)	$t(k)$	CW(k)	$t(k)$	CW(k)	$t(k)$	CW(k)
1 month	**0.090**	**0.062**	0.104	**0.046**	0.952	0.456	0.916	0.482
3 months	0.104	**0.054**	0.112	**0.038**	1.000	0.908	0.998	0.854
4 months	0.110	**0.056**	0.114	**0.040**	1.000	0.976	1.000	0.942
6 months	0.120	**0.056**	0.116	**0.038**	1.000	0.996	0.998	0.982
9 months	0.118	**0.052**	0.114	**0.046**	1.000	0.998	1.000	0.988
12 months	0.132	**0.052**	0.120	**0.052**	1.000	0.998	1.000	0.994
24 months	0.146	**0.066**	0.112	**0.068**	0.996	0.998	0.978	0.984
36 months	0.134	**0.068**	0.112	**0.074**	0.986	0.990	0.942	0.932
48 months	0.148	**0.066**	0.124	**0.070**	0.954	0.958	0.906	0.834
60 months	0.154	**0.090**	0.142	**0.080**	0.912	0.974	0.854	0.862
JS	**0.058**	**0.008**	**0.050**	**0.012**	0.798	0.790	0.760	0.690

Notes: CW(k) indicates the statistic provided by Clark and West (2007) where k is the forecast horizon. JS indicates a joint statistic. $r^1_{k,t}$ and $r^2_{k,t}$ are aggregate returns and excess returns, respectively. Boldface values indicate significance at the 10 per cent level.

nominal size, 0.10, when the forecast horizon is less than 12 (60) months. The size distortion of t statistic is mild if forecast horizons are greater than 9 (48) months for aggregate (excess) returns. Except for the forecast horizon of five years, the size of CW statistic lies between 0.052 and 0.068 for aggregate returns and 0.038 and 0.074 for excess returns. The above results based on the block bootstrap indicate that t statistic tends to over-reject the non-predictability hypothesis when the forecast horizon is greater than one year, but CW statistic is conservative in general. However, the slight size distortion of t test in long horizon should not affect the conclusions of Table 4 since p values in Table 4 are very small (less than 0.02). Moreover, CW statistics are conservative since their sizes are far below 1.0 and hence rejecting the non-predictability hypothesis of stock returns by CW statistics in Table 4 indicates fairly strong evidence of rejecting the hypothesis. It is worth noting that the p value of CW_{max} in Table 4 exceeds 0.1 (0.102) for excess returns, but this should indicate significance given a small size of CW_{max} (0.012). Because of ignoring the information of DGP, results from the block bootstrap (Table 6) are slightly worse than those from the residual bootstrap (Table 5), which is also consistent with findings in Cameron *et al.* (2008).

In short, results from Table 4 are in general consistent with those of Table 3. Results from Table 6 are in general consistent with those of Table 5 except for joint statistics. This paper therefore concludes that the predictability of UK's stock returns is visible in the short run without macro-variables if the forecast horizon exceeds four months.

5 Conclusions

Can dividend yields out-predict UK's stock returns without short rates? This question was investigated using monthly data from the UK's stock markets over the period from 1923 to 2007. The sample period of this paper is the longest one in related literature. This paper modeled the dynamics of dividend yields with a non-linear ESTAR process and found that UK's dividend yields support the non-linear specification. This work then applied a bootstrap test to examine the predictability of UK's stock returns based on a bootstrap test. The current research found that the predictability of UK's stock returns was visible without short rates if the forecast horizon was greater than four months. The above finding is crucial since the literature did not observe short-term out-predictability of UK stock returns.

An alternative source of non-linearity may come from the prediction equation itself. The long-horizon prediction equation may have an ESTAR specification. This paper does not investigate this possibility due to the technical difficulty in performing multi-steps-ahead forecasts of an ESTAR model as pointed out by Granger and Teräsvirta (1993). Additionally, an ESTAR specification of the return prediction equation is not supported empirically if the forecast horizon is less than nine months.[14]

Appendix A

This appendix describes the bootstrapping procedure for constructing finite-sample distribution of in-sample tests. The procedure includes the following steps.

1. This paper estimates equation (1) under the hypothesis of no return predictability ($\beta_k = 0$) via ordinary least squares, and estimates equation (2) with the lag order determined by Akaike information criterion using non-linear least squares. Given these parameter estimates and estimated residuals, the DGP under the assumption of no return predictability is given as follows:

$$r_{1,t-1}^{j} = \hat{\alpha}_1^j + \tilde{\varepsilon}_{1t}^j \qquad j = 1, 2$$

$$w_t = \hat{b} + \left\{\exp\left[\hat{\theta} * \left(w_{t-1} - \hat{b}\right)^2\right]\right\} * \left[\hat{\alpha} * \left(w_{t-1} - \hat{b}\right) + (1 - \hat{\alpha}) * \left(w_{t-2} - \hat{b}\right)\right] + \tilde{\varepsilon}_t \quad \text{(A1)}$$

where $r_{1,t}^1 \equiv \log[(P_{t+1} + D_{t+1})/P_t]$, $r_{1,t}^2 = r_{1,t}^1 - r_t^f$ and $\hat{\alpha}_1^j$, $\hat{b}$ and $\hat{\theta}$ are parameter estimates.

2. Let $\hat{\varepsilon}_{1t}^j$ and $\hat{\varepsilon}_{2t}$ be estimated residuals from ordinary least squares. This work randomly draws T + 1000 disturbances, with replacements, from the estimated residuals, $\hat{\varepsilon}_t^j = \left(\hat{\varepsilon}_{1t}^j, \hat{\varepsilon}_{2t}\right)'$, to generate a series of residuals, $\tilde{\varepsilon}_t^j = \left(\tilde{\varepsilon}_{1t}^j, \tilde{\varepsilon}_{2t}\right)'$, for our pseudo-sample. This paper draws the residuals, $\hat{\varepsilon}_{1t}^j$ and $\hat{\varepsilon}_{2t}$, in tandem, so that the simulated sample preserves the contemporaneous correlation in the disturbances presented in the original data. Given the parameter estimates, generated residuals

[14]Results are not reported here but are available upon request from authors.

and initial value of w_{t-1} and w_{t-2}, this research generates the pseudo-sample of $r^j_{1,t}$ and w_t based on equation (A1). The initial values of w_{t-1} and w_{t-2} are set to zero and the first 1000 observations are dropped. After generating the pseudo-sample for $r^j_{1,t}$ and w_t, this paper constructs $r^j_{k,t}$ for $j = 1, 2$ as follows: $r^j_{k,t} \equiv \sum_{i=1}^{k} r^j_{1,t+i-1}$ and then estimates equation (1) at different forecast horizons.

3. Computes the t statistic for the slope coefficient of equation (1), $t(k)$, and the largest t statistic among 10 forecast horizons, $t_{\max} = \max\{t(k)\text{: } k = 1, 3, 4, 6, 9, 12, 24, 36, 48, 60\}$.
4. After repeating the procedure in steps 2 and 3 1000 times, this paper obtains the finite-sample distribution of the in-sample $t(k)$ statistic.

Appendix B

This appendix describes the three-step procedure provided by Kilian (1999) and Rapach and Wohar (2005).

1. The DGP of stock returns and dividend yields are given as follows:

$$r^j_{1,t-1} = \hat{\alpha}^j_1 + \tilde{\varepsilon}^j_{1t} \qquad j = 1, 2$$

$$w_t = b + (w_{t-1} - b)\exp\left[\theta(w_{t-1} - b)^2\right] + \hat{\varepsilon}_{2t}$$

   This paper generates pseudo-data for returns and dividend yields based on Monte-carlo simulations where the pseudo-residuals are randomly drawn from a standard normal distribution.
2. Based on the pseudo-data simulated from step 1, this work constructs different test statistics at different forecast horizons and bootstraps their finite-sample distributions with 500 replications with the procedures described in Appendix A.
3. After repeating the previous procedures 500 times, this paper obtains the size of bootstrap tests.

Appendix C

This appendix describes the procedures of the moving block bootstrap of Künsch (1989), with a block size m, to construct the finite-sample distribution of in-sample tests. A detailed discussion of this method can be found in Künsch (1989). The procedures include the following steps.

1. Given the data of $r^j_{1,t}$ and w_t for $j = 1, 2$, this paper first constructs k horizon returns as $r^j_{k,t} \equiv \sum_{i=1}^{k} r^j_{1,t+i-1}$ in which $r^1_{1,t} \equiv \log[(P_{t+1} + D_{t+1})/P_t]$, $r^2_{1,t} = r^1_{1,t} - r^f_t$. This paper regresses $r^j_{k,t}$ on w_t to obtain the estimate of β_k and its t value ($\hat{\beta}_k$ and $\hat{t}(k)$), respectively, for $k = 1, 3, 4, 6, 9, 12, 24, 36, 48$ and 60.
2. Define the vector $x^j_t = (r^j_{k,t}, w_t)'$ that collects the dependent and the explanatory variables for each observation. Let m ($1 \le m < T$) be a block length, and let $B_{t,m} = (x^j_t, x^j_{t+1}, \ldots, x^j_{t+m-1})$ be the block of m consecutive observations starting at x^j_t. The moving block bootstrap draw $b_0 = T/m$ blocks randomly with replacements from the set of overlapping blocks $\{B_{1,m}, \ldots, B_{T-m+1,m}\}$ to generate

our pseudo-sample, $\{\tilde{x}_t^j\}_{t=1}^T$. After generating the pseudo-sample for $\tilde{r}_{k,t}^j$ and $\tilde{w}_t$, this work estimates equation (1) at different forecast horizons to obtain the estimate of β_k ($\tilde{\beta}_k$) and then constructs the following statistics:

$$\tilde{y}(k) = \left[\tilde{\beta}(k) - \hat{\beta}(k)\right] / \sigma_{\tilde{\beta}(k)}$$

3. After repeating the procedure in steps 2 1000 times, this paper obtains the finite-sample distribution of, $\tilde{y}(k)$. Künsch (1989) shows that the distribution of $\hat{t}(k)$ can be approximated asymptotically by the distribution of $\tilde{y}(k)$.

To evaluate the size and power of bootstrap tests based on block bootstrap method, this paper adopts the following three step procedures.

(a) The DGP of stock returns and dividend yields are given as follows:

$$r_{1,t-1}^j = \hat{\alpha}_1^j + \tilde{\varepsilon}_{1t}^j \qquad j = 1, 2$$

$$w_t = b + \left\{\exp\left[\theta * (w_{t-1} - b)^2\right]\right\} * [\alpha * (w_{t-1} - b) + (1 - \alpha) * (w_{t-2} - b)] + \varepsilon_t$$

This paper generates pseudo-data for returns and dividend yields based on Monte-Carlo simulations where the pseudo-residuals are randomly drawn from a standard normal distribution.

(b) Based on the pseudo-data simulated from step (a), this work constructs k horizon returns as $r_{k,t}^j \equiv \sum_{i=1}^k r_{1,t+i-1}^j$, and then estimates equation (1) to obtain different test statistics at different forecast horizons. The current research then bootstraps finite-sample distributions of test statistics with 500 replications with the procedures described in Appendix C.

(c) After repeating the previous procedure in (a), (b) and (c) 500 times, this paper obtains the size of bootstrap tests.

As for the power of bootstrap tests, the DGP in step (a) is the same as those of equation (7). Following the same procedure in steps (a), (b) and (c), this work obtains the power of bootstrap tests.

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