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Does the Macroeconomy Predict U.K. Asset Returns in a Nonlinear Fashion? Comprehensive Out-of-Sample Evidence

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Abstract

We perform a comprehensive examination of the recursive, comparative predictive performance of a number of linear and non-linear models for UK stock and bond returns. We estimate Markov switching, threshold autoregressive (TAR), and smooth transition autoregressive (STR) regime switching models, and a range of linear specifications in addition to univariate models in which conditional heteroskedasticity is captured by GARCH type specifications and in which predicted volatilities appear in the conditional mean. The results demonstrate that U.K. asset returns require non-linear dynamics be modeled. In particular, the evidence in favor of adopting a Markov switching framework is strong. Our results appear robust to the choice of sample period, changes in the adopted loss function and to the methodology employed to test the null hypothesis of equal predictive accuracy across competing models.

Keywords: regime switching, threshold, smooth transition, predictive regressions, forecasting.
JEL code: C53, E44, G12, C32.
Word Count: 10,582

1. **Introduction**

Empirical research over the past two decades has seen a huge increase in interest in non-linear dynamics in macroeconomic and financial time-series. Although the belief in the non-linear (asymmetric, across up- and down-moves) behaviour of the business cycle has been long-held (e.g., Keynes, 1936), it is only over this recent time frame that a consistent body of work has been established examining and testing such dynamics. Arguably, this was initiated by business cycle researchers (see, for example, DeLong and Summers, 1986; Falk, 1986; Sichel, 1989, 1993; Teräsvirta and Anderson, 1992; Beudry and Koop, 1993) and was then extended to the search for non-linear dynamics within financial variables, including stock returns (see, for example, Martens, Kofman and Vorst, 1998; Perez-Quiros and Timmermann, 2000; Leung et al, 2000; Maasoumi and Racine, 2002; Shively, 2003 and Bredin and Hyde, 2005) and interest rate dynamics (e.g.,

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Balke and Fomby, 1997; Enders and Granger, 1998; van Dijk and Franses, 2000; Enders and Siklos, 2001; McMillan, 2004).

Concurrently, empirical research has also been devoted to the examination of the links between macroeconomic and financial variables and in particular to tests of whether the former can forecast the latter. Although, this line of research has an established history (see, for example, Keim and Stambaugh, 1986; French, Schwert and Stambaugh, 1987; Fama and French, 1989; Balvers, Cosimano and McDonald, 1990; Cochrane, 1991; Campbell and Hamao, 1992), interest has been renewed following the work of Pesaran and Timmermann (1995), who forcefully argued in favour of predictability. Interestingly, a portion of this research has examined in depth the forecastibility of UK stock and bond returns (or interest rates), see e.g., Artis, Banerjee, and Marcellino (2005), Pesaran, Schuermann, and Smith (2009), and Pesaran and Timmermann (2000). The main implications of this literature when applied to UK data have been similar to the typical findings of the ever expanding research concerning linear predictability from macroeconomic variables to asset returns (see e.g., Ang and Bekaert, 2007 or Timmermann, 2008): linear predictability tends to be "elusive", i.e., subject to frequent structural changes and very hard to exploit in practice because—due to the presence of breaks and instability—it tends to be hard to forecast the appearance and structure of the very predictability patterns one would like to exploit.

Inevitably, these two lines of research merged, with the search for financial asset return, and particularly stock return, predictability from macroeconomic variables within a non-linear framework. This work largely began in earnest with the papers by Perez-Quiros and Timmermann (2000), McMillan (2001) and Maasoumi and Racine (2002) who used prominent non-linear models, such as the Markov-switching, smooth-transition and threshold regression approaches. However, it remains an open question whether the non-linear approach to predictability modelling provides any substantial benefit over the linear alternative. That is, within the many forecasting exercises that have appeared in the literature, the evidence is not definitive as to whether improvements in forecasting power are always evident with the non-linear approach. An equivalent way to approach this question is by asking whether there can be any value in trying to estimate more complicated models that capture the existence of regimes and instability in the linear predictability relationships that connect macroeconomic variables to financial returns. Thus, the aim of this paper is to reconsider the evidence regarding the usefulness of non-linear forecasts for UK stock and bond returns. In particular, we wish to seek answer to the question of whether non-linear modelling of prediction regressions linking financial asset returns to macroeconomic variables may provide for significantly improved forecasting performance over a linear alternative. Previous evidence for the UK has suggested that such an approach may prove fruitful, although the approach adopted here is intended to be more systematic and complete than the previous research, both in terms of the models considered and the forecast evaluation metrics.

With regard to previous research on UK data, there is now a long list of papers that have investigated whether nonlinear econometric models may provide any payoffs in the forecasting space when applied to financial returns. Needless to say, by using different data, sample periods, research designs (to perform their recursive out-of-sample assessments), and especially heterogeneous modelling approaches, these papers have reached wildly different conclusions as to the usefulness of nonlinear models. For instance, Sarantis (2007) has predicted UK stock returns using smooth transition autoregressive (STR) models. McMillan (2001) demonstrates that a smooth-transition model for dividend yield predictability of stock returns provides an improved in-sample fit over a linear predictive regression. McMillan (2003) similarly demonstrates the usefulness of the smooth-transition model in predicting UK stock returns with a variety of macroeconomic variables, thus using a similar context to this paper. However, the forecasting exercise in McMillan (2003) is limited in terms of breadth of models entertained and of metrics employed (considering only the root mean squared error) in comparison to the extensive exercise here. Bredin and Hyde (2005) show that the improvement in forecasting performance of the non-linear smooth transition model for UK stock returns (as well as seven other markets) is largely limited to direction (sign) forecasting, but overall, there is little improvement over the linear model. Further evidence on the need to model non-linear dynamics is provided by Guidolin and Timmermann (2003, 2005) and Guidolin and Hyde (2008, 2009) who employ a Markov-switching approach. Guidolin and Timmermann (2003) demonstrate that accounting for regimes in U.K. stock returns leads to improved forecasting performance, while Guidolin and Timmermann (2005) establishes the need for nonlinear dynamics in both stock and bond returns and that the predictability from such models yields considerable effects on optimal asset allocation.[1]

Needless to say, even though each of the papers listed above did pursue a valuable goal in exploring in depth the forecasting performance (or the economic value, for instance in dynamic asset allocation applications) of specific nonlinear families of models, there are inherent limits in a literature that has so far refrained from performing a systematic assessment of the predictive, out-of-sample potential of simple linear models, relatively complex nonlinear frameworks, and a few standard benchmarks typical of the forecasting literature. This paper seeks to improve upon the existing literature on the predictability of UK financial series in two ways. First, we consider a wider set of non-linear models than the above cited papers, including both the smooth-transition and Markov-switching models, but also including threshold and ARCH models. As we have seen, most of these models has been considered in isolation by specific papers, but a genuine, wide-ranging horse race involving these alternative non-linear frameworks is novel. In fact, we also introduce a new family of logistic smooth-transition models in which the transition variable is not simply selected to correspond to one of the predictors, but it is instead assumed to be either a linear prediction for the asset return series to be forecast or a GARCH-style variance prediction to be jointly obtained (estimated) with the smooth-transition conditional mean model itself. Second, we entertain a wider range of forecast evaluation metrics than considered in the above papers, including standard measures of the forecast error, measures of forecast equality and measures of the forecast sign. In particular, we do not limit ourselves to rank models based on their recursive out of sample predictive accuracy, but also deploy an array of formal

[1]There is also a growing literature that has shown the existence of nonlinear dynamics in higher-order moments in UK financial returns, especially in stock return volatility. See e.g., Alexander and Lazer (2009). However, in our paper we are mostly interested in forecasting the level (mean) of asset returns, although it is clear that economic applications will often equally benefit from precise and timely forecasts of the entire density of returns, as in Guidolin and Timmermann (2005).

testing procedures to test whether our UK financial data contain any evidence allowing us to reject the null of no differential predictive accuracy between linear and non-linear models.

To highlight our key findings we find strong evidence that non-linear models not only provide better predictive performance than linear specifications for both stocks and bonds do, but also that that performance is significantly better in a statistical sense. In particular, we find convincing evidence in support of Markov switching-type non-linear models. Other nonlinear frameworks (e.g., a Logistic STR model in which switches are governed by one lag of a short-term interest rate) offer appreciably accurate forecasting performances, but these other models that have been widely studied in the literature rarely represent a threat to the accuracy of relatively simple, Markov switching predictive regressions. In particular, Diebold-Mariano tests show that Markov switching models consistently outperform all other models, both linear and non-linear. The exceptions are few and essentially simply that under a square loss function it may hard to tell apart the Markov switching models from a few Logistic STR models. While this finding holds irrespective of the assumed loss function (square and the linex) in the case of bond return forecasts, this is not the case for stock return forecasts, where the finding of diffuse rejections of the null hypotheses of equal predictive accuracy involving the Markov switching models applies only under a square loss function. In a sense, this can be taken to imply that bond returns are "easier" to predict (better than simple linear models do) than stock returns are. Additional (Giacomini and White, 2006) tests that avoid some of the statistical limitations affecting the classical Diebold-Mariano tests, lead to another interesting qualification, that also applies to bond return forecasts: the data may not contain sufficient evidence of heterogeneous recursive predictive performance at a 12-month horizon, when models seem instead to become very hard to tell apart. However, our baseline finding that for short prediction horizons, bond returns (and to some extent, stock returns) can be predicted more accurately using nonlinear frameworks (and especially Markov switching models) appears robust to all these tests and further robustness checks, detailed in the main body of the paper.

The remainder of the paper is set out as follows: Section two presents the various forecasting models considered while section three provides details of the evaluation metrics. Section four describes the data. The main empirical results and several robustness checks are presented and analysed in section five. Section six concludes.

2. **The Forecasting Models**

Our objective is to investigate a comprehensive set of alternative linear and non-linear specifications. The selected models cover standard benchmarks, linear models, GARCH and non-linear regime switching and threshold models. Since many of these models are common in the literature we only review them briefly.

2.1. *Linear, GARCH-type and benchmark models*

In the class of linear models, we first consider a simple linear regression that projects asset returns at time $t+h$ ($h \geq 1$) on the macroeconomic variables that belong to the time t information set ($\mathcal{I}_t$)

$$r^j_{t+h} = \alpha^j_h + (\beta^j_h)'\mathbf{X}_t + \epsilon^j_{t+h}, \tag{1}$$

where j equals either s (stocks) or b (bonds), $\mathbf{X}_t \equiv [r^j_t \; dy_t \; \Delta i_t \; TERM_t \; \Delta s_t \; \Delta oil_t \; \pi_t \; \Delta ip_t \; \Delta u_t]'$, and ϵ^j_{t+h} is a martingale difference sequence.[2] The unknown parameters α^j_h and β^j_h are indexed by both the forecast horizon, h, and by the asset market under analysis, j, whether stock or bond. Potential autoregressive effects in Equation (1) are accounted for by the inclusion of the current, time t value of the asset return r^j_t, in the vector of predictors $\mathbf{X}_t$. Linear models such as Equation (1) are the bedrock of the predictability literature, see Guidolin and Ono (2006), Rapach, Wohar, and Rangvid (2005) and references therein.

The choice of prediction variables is driven by prior empirical literature on macro factors and predictability. While much initial evidence derives from the U.S., e.g., Chen, Roll and Ross (1986) and Fama and French (1988, 1989), in the U.K., Poon and Taylor (1991), Clare and Thomas (1994), Black and Fraser (1995) and Pesaran and Timmermann (2000) establish the importance of several macroeconomic factors for explaining and predicting stock returns including inflation, industrial production, oil price changes, the term spread, interest rates, and the dividend yield. Moreover, these variables relate to our intuitive financial understanding as these are the variables that would impact upon the cash flows or discount rates of the financial assets and therefore we would expect there to be a potential relationship. For example, variables such as output or unemployment would have a direct impact on a firm's earnings and therefore its dividend payments and hence an effect on its share price. Similarly, variables such as inflation and interest rates would have a direct impact on the discount rate at which cash flows are discounted to establish the price of both stocks and bonds, and of course, each variable may have an indirect impact upon cash flows and discount rates.

We also consider augmenting the linear specification by allowing time-varying predictions of asset return volatility to affect conditional mean forecasts. Specifically we estimate GARCH-in-Mean models

$$r^j_{t+h} = \alpha^j_h + (\beta^j_h)'\mathbf{X}_t + \gamma\hat{\sigma}^j_{t+h} + \epsilon^j_{t+h}, \tag{2}$$

where $\hat{\sigma}^j_{t+h}$ is a prediction at time t of the volatility of the return of asset j at time $t+h$. We consider three alternative specifications for the conditional variance, a GARCH(1,1), an EGARCH(1,1) and a Threshold GARCH(1,1). Further we also estimate each of these specifications assuming the residuals are distributed (i) normally and (ii) student-t. In the latter case, the parameter capturing the number of degrees of freedom is also estimated by MLE.

[2] The predictor variables contained with the vector $\mathbf{X}_t$ are precisely defined in Section 4. Running quickly through the list, they are the lagged asset return, the dividend yield, the change in short-term nominal rate, the riskless term spreads, the change in log-effective exchage rate, the change log-price of oil, the inflation rate, and the change in unemployment rate.

Finally, we supplement these linear frameworks, with a number of standard benchmarks prevalent in the literature. These are a simple a random walk with drift model and a basic autoregressive model, both with and without the addition of GARCH-in-Mean effects.

2.2. *Markov Switching Models*

The financial press often refers to the existence of financial market states as "bull" and "bear" markets, see Guidolin and Timmermann (2005). Consequently we allow the predictive relationship between stock and bond returns and a set of macroeconomic variables to depend on a set of unobservable states that follow a first-order Markov process:

$$r^j_{t+h} = \alpha^j_{h,S_t} + (\beta^j_{h,S_t})'\mathbf{X}_t + \epsilon^j_{t+h} \quad \epsilon^j_{t+h}|\mathcal{I}_t \sim N(0, h^j_{t+h,S_t}), \tag{3}$$

where the constant α^j_{h,S_t}, the regression coefficients in β^j_{h,S_t}, and the variance h^j_{t+h,S_t} all depend on an *unobservable* state variable S^j_t, an indicator variable taking values $1, 2, ...k$, where k is the number of states. We consider both the homoskedastic case i.e., the variance is independent of the state (MS model, $h^j_{t+h,S_t} = h^j_{t+h}$) and also the presence of heteroskedasticity in the form of regime-specific variances (MSH model). We assume that S^j_t follows a first-order Markov chain with moves between states governed by a constant transition probability matrix, $\mathbf{P}^j$, with generic element p^j_{il} defined as

$$\Pr(S^j_{t+1} = l|S^j_t = i) = p^j_{il}, \quad i, l = 1, .., k, \tag{4}$$

i.e., the probability of switching to state l between t and $t + 1$ given that at time t the market is in state i. We impose and estimate simple two-state predictive regressions in which $k = 2$. From an economic viewpoint, this restriction implies that financial markets may switch between two alternative predictive environments, so that, for instance, while some predictors may affect subsequent asset returns in one of the two regimes, this does not have to be the case in the remaining regime. Moreover, while a given predictor may affect future asset returns with a sign in one regime, the model is flexible enough to accommodate an impact with opposite sign in the other regime.[3]

2.3. *Threshold and Smooth Transition Regime Switching Models*

An alternative approach to Markov switching models where the switching variable remains unobservable is the family of non-linear regime-switching models where the transition variable is observed. First, we consider the Heaviside threshold (TAR) model of Tong (1983) that allows for abrupt switching depending

[3] We also impose two further restrictions. First, we estimate the properties of the Markov state separately for stock and bond markets in each country (hence the notation S^j_t). Second, when the variance is allowed to depend on the state, we restrict both the conditional mean framework and the conditional variance to be governed by a single state variable, S^j_t.

on whether the transition variable is above or below the threshold:

$$\begin{aligned} r^j_{t+h} &= [I^j_t \alpha^j_{h,1} + (1 - I^j_t)\alpha^j_{h,2}] + [I^j_t \beta^j_{h,1} + (1 - I^j_t)\beta^j_{h,2}]'\mathbf{X}_t + \epsilon^j_{t+h} \quad \epsilon^j_{t+h} \sim IIN(0, h^j_h), \\ I_t &= \begin{cases} 1 & \text{if} \quad g(\mathbf{X}_t) > c_j \\ 0 & \text{if} \quad g(\mathbf{X}_t) \leq c_j \end{cases}, \end{aligned} \tag{5}$$

i.e. each of the two regimes applies dependent on whether $g(\mathbf{X}_t)$, a function of the predictors in $\mathbf{X}_t$, exceeds or not an estimated threshold c_j.[4] For instance, the logic of a TAR model may be as follows: high IP growth has a negative effect on future bond returns as long as monetary policy is tight, as revealed by the fact that short-term rates exceed some (endogenously determined) threshold c_j; otherwise high IP growth rates forecast positive future bond returns.

In addition to TAR models we also consider smooth transition regression models. Whilst the TAR model imparts an abrupt non-linear behavior dependent on the threshold variable(s), the smooth-transition model allows for possible gradual movement between regimes. These models capture two types of adjustment. First, the parameters of the model change depending upon whether the transition variables is above or below the threshold value. Second, the parameters of the model change depending upon the distance between the transition variable and the threshold value. The general STR model is given by

$$r^j_{t+h} = \alpha^j_{h,1} + (\beta^j_{h,1})'\mathbf{X}_t + [\alpha^j_{h,2} - \alpha^j_{h,1} + (\beta^j_{h,2})'\mathbf{X}_t - (\beta^j_{h,1})'\mathbf{X}_t]F(\mathbf{e}'_i\mathbf{X}_t) + \epsilon^j_{t+h} \quad \epsilon^j_{t+h} \sim IIN(0, h^j_h), \tag{6}$$

where $0 \leq F(\mathbf{e}'_i\mathbf{X}_t) \leq 1$ is the transition function and the i-th variable in $\mathbf{X}_t$ (selected by the product $\mathbf{e}'_i\mathbf{X}_t$) acts as the transition variable.[5] The smooth transition is perhaps theoretically more appealing than threshold models that impose an abrupt switch in parameter values since traders are likely to switch their trading patterns at slightly different times (thus leading to smooth transitions in asset return dynamics) rather than all simultaneously (abrupt transition).

The STR model allows different types of market behavior depending on the nature of the transition function. Among the possible transition functions, the logistic has received considerable attention in the literature because it allows differing behavior depending on whether the transition variable is above or below the threshold value and is given by the following, where the full model is referred to as the Logistic STR (or LSTR) model

$$F(\mathbf{e}'_i\mathbf{X}_t) = \frac{1}{1 + \exp(-\rho_j(\mathbf{e}'_i\mathbf{X}_t - c_j))} \quad \rho_j > 0, \tag{7}$$

ρ_j is an estimated smoothing parameter and c_j is the estimated threshold. This function allows the parameters to change monotonically with $\mathbf{e}'_i\mathbf{X}_t$. In the limit, as $\rho_j \to \infty$, $F(\mathbf{e}'_i\mathbf{X}_t)$ becomes a Heaviside function and Equation (6) reduces to the TAR model; as $\rho_j \to 0$, Equation (6) becomes linear.

[4]In the simplest case the function $g(\cdot)$ simply extracts one (threshold) variable from $\mathbf{X}_t$. Our baseline TAR model is homoskedastic, i.e., governed by independently and identically normally distributed random shocks. We have also experimented with heteroskedastic versions, finding qualitatively similar out-of-sample prediction performance.

[5]As with the TAR model, $F(\mathbf{e}'_i\mathbf{X}_t)$ can be generalized to $F(g(\mathbf{X}_t))$.

Still within the STR class, the exponential function allows differing behavior depending on the distance from the threshold value, with the resulting model referred to as the Exponential STR (or ESTR) model,

$$F(\mathbf{e}_i'\mathbf{X}_t) = 1 - \exp(-\rho_j(\mathbf{e}_i'\mathbf{X}_t - c_j)^2) \quad \rho_j > 0, \tag{8}$$

where the parameters in Equation (8) change symmetrically about c_j as $\mathbf{e}_i'\mathbf{X}_t$ changes. If $\rho_j \to \infty$ or $\rho_j \to 0$ the ESTR model becomes linear, while capturing non-linear dynamics requires finite values for ρ_j. This model implies that the dynamics obtained for values of the transition variable close to c_j differ from those obtained for values that largely differ from c_j.

Given the difficulty in estimating the smoothing parameter, ρ_j, we follow Teräsvirta and Anderson (1992) and scale the smoothing parameter by the standard deviation of the transition variable in the case of LSTR, and by the variance of the transition variable in the ESTR case. Further, a key decision is the choice of the transition variable. Over the in-sample period we estimate each of the TAR, LSTR and ESTR models in turn with a different transition variable corresponding to each predictor in $\mathbf{X}_t \equiv [r_t^j \ dy_t \ \Delta i_t \ TERM_t \ \Delta s_t \ \Delta oil_t \ \pi_t \ \Delta ip_t \ \Delta u_t]'$ and select the variable that produces the smallest sum of squared residuals. In order to select the threshold value for TAR models, we follow the general procedure in Chan (1993) where possible threshold values (from the middle 70% of the ordered series) are selected with the models in Equations (5) and (6) estimated and the threshold chosen as the one that minimizes the sum of squared residuals. In addition to the above procedures we also consider a further transition variable: a prediction of the dependent variable rather than just using one (or a combination of) the predictors. Specifically, we estimate a linear version of the predictive regression model (i.e., Equation (1)) and obtain the fitted values for the dependent variable, which are in turn used as the transition variable in the TAR and STR models. These models are often abbreviated as TAR-SRF and STR-SRF in Section 5. Finally, we also estimate a LSTR-GARCH model and allow the fitted GARCH(1,1) variance to act as the transition variable

$$\begin{aligned} r_{t+h}^j &= \alpha_{h,1}^j + (\beta_{h,1}^j)'\mathbf{X}_t + [\alpha_{h,2}^j - \alpha_{h,1}^j + (\beta_{h,2}^j)'\mathbf{X}_t - (\beta_{h,1}^j)'\mathbf{X}_t]F(\mathbf{e}_i'\mathbf{X}_t) + \epsilon_{t+h}^j, \\ h_{t+1}^j &= \omega^j + \zeta^j(\eta_t^j)^2 + \theta^j h_t^j \qquad F(\mathbf{e}_i'\mathbf{X}_t) = \left[1 + \exp\left(-\rho_j \frac{h_t^j - c_j}{\sigma(h_t^j)}\right)\right]^{-1}, \end{aligned} \tag{9}$$

in which ϵ_t^j is assumed to be conditionally normal, and $\epsilon_t^j | \mathcal{I}_t \sim N(0, h_t^j)$, so that η_t^j is standard normal. In Equation (9) the regimes switches are defined according to the fact that the volatility is currently predicted to be high or low. Such a model is only estimable with the STR conditional mean model, where joint estimation is required in order to obtain the transition value c_j. Equation (9) becomes comparable to Markov switching heteroskedastic models in Equation (3) because the second moment contributes to the definition of the regime, along with the conditional mean. This models are abbreviated as STR-GARCH(1,1) in Section 5.[6]

[6] In all models the delay parameter in the transition function is set to be equal to one rather than estimated since it is recommended that the delay lag is no greater than the lag length of the explanatory variables, which is chosen to be one for the case $h = 1$.

3. **Evaluation Methodologies: Testing for Superior Predictive Accuracy**

To evaluate the forecasting outcomes from the various linear and non linear models, we employ a wide array of alternative performance measures and procedures for testing the null of equal predictive accuracy across pairs of models. Here, we briefly describe these measures and testing methodologies.

Define the time t forecast error from model μ, at horizon h, and for asset j (i.e., stocks or bonds) as

$$e_{t,t+h}^{j,\mu} = r_{t+h}^{j} - \hat{r}_{t,t+h}^{j,\mu}, \tag{10}$$

where $\hat{r}_{t,t+h}^{j,\mu}$ comes from any of the 25 alternative models – linear and non-linear – defined in Section 2. For each combination defined by market, model, and horizon, we proceed to compute six different measures of prediction accuracy ("performance"):

1. **Root Mean Squared Forecast Error (RMSFE).** The RMSFE is computed as

$$RMSFE_{h}^{j,\mu} \equiv \sqrt{\frac{1}{T-h}\sum_{t=1}^{T-h}(e_{t,t+h}^{j,\mu})^2}, \tag{11}$$

   where T is the total sample size available for the recursive out-of-sample prediction exercise.

2. **Forecast Error Bias.** The bias is just the signed sample mean of all forecast errors:

$$Bias_{h}^{j,\mu} \equiv \frac{1}{T-h}\sum_{t=1}^{T-h} e_{t,t+h}^{j,\mu}. \tag{12}$$

   Clearly, a large, signed value of the bias indicates a systematic tendency of a forecast function to either over- or under-predict asset returns.

3. **Forecast Error Variance (FEV).** While the definition is obvious,

$$FEV_{h}^{j,\mu} \equiv \frac{1}{T-h}\sum_{t=1}^{T-h}(e_{t,t+h}^{j,\mu})^2 - \left[\frac{1}{T-h}\sum_{t=1}^{T-h} e_{t,t+h}^{j,\mu}\right]^2 = \frac{1}{T-h}\sum_{t=1}^{T-h}(e_{t,t+h}^{j,\mu})^2 - [Bias_{h}^{j,\mu}]^2, \tag{13}$$

   one useful fact is that $FEV_{h}^{j,\mu} + [Bias_{h}^{j,\mu}]^2 = MSFE_{h}^{j,\mu}$, i.e. large MSFEs (poor performance) may derive from either high forecast error variance or from large average bias.

4. **Mean Absolute Forecast Error (MAFE).** The formula is similar to the RMSFE, with the difference that signs are neutralized using absolute values and not by squaring:

$$MAFE_{h}^{j,\mu} \equiv \frac{1}{T-h}\sum_{t=1}^{T-h}\left|e_{t,t+h}^{j,\mu}\right|. \tag{14}$$

   As it is well known, this statistics is more robust to the presence of outliers than RMSFE.

5. **Mean Percent Forecast Error (MPFE).** MPFE measures the sample mean of errors expressed as a percentage of the realized values:

$$MPFE_h^{j,\mu} = \frac{1}{T-h}\sum_{t=1}^{T-h}\frac{e_{t,t+h}^{j,\mu}}{r_{t+h}^{j}}. \tag{15}$$

Similarly to the bias statistic, also MPFE is a signed measure of prediction accuracy – the only difference being that MPFE is a scaled measure.

6. **Success Ratio (SR).** The success ratio is the proportion of times that the sign of r_t^j and of a forecast from a given model μ are the same:

$$SR_h^{j,\mu} = \frac{1}{T-h}\sum_{t=1}^{T-h} I_{\{r_{t+h}^{j}\hat{r}_{t,t+h}^{j,\mu}>0\}}, \tag{16}$$

where $I_{\{r_{t+h}^{j}\hat{r}_{t,t+h}^{j,\mu}>0\}}$ is an indicator variables that take unit value when r_{t+h}^{j} and $\hat{r}_{t,t+h}^{j,\mu}$ have the same sign. As often argued in empirical finance, for many trading strategies it is more important that a forecast function may deliver predictions with a correct sign than predictions which are quantitatively very accurate (i.e., it may be better to miss the forecast by much getting the sign of the future return right than missing the sign and proposing a relatively accurate forecast with an incorrect sign indication).

However a basic ranking of forecasting models based on any of these six measures is unlikely to prove decisive: the fact that model $\mathcal{M}_1$ proves more accurate than model $\mathcal{M}_2$ does not imply that the null hypothesis that the difference between $\mathcal{M}_1$ and $\mathcal{M}_2$ is zero may be rejected in statistical terms. Consequently, we employ four different methodologies to test whether any differences may be supported in statistical terms. First, we consider the Mincer and Zarnowitz (1969) regression:

$$r_{t+h}^{j} = \varphi_{h,0}^{j} + \varphi_{h,1}^{j}\hat{r}_{t,t+h}^{j,\mu} + \xi_{t,t+h}^{j,\mu}, \tag{17}$$

where $\xi_{t,t+h}^{j,\mu}$ is a martingale difference sequence with constant variance σ_{ξ}^2. A "good" (sometimes said to be unbiased) forecast model implies that $\varphi_{h,0}^{j} = 0$ and $\varphi_{h,1}^{j} = 1$; and also the regression R^2 should be high, ideally close to one (i.e., a good forecast function ought to explain most of the variation in the predicted variable). Hence we report: (i) the R^2 from regression (17); (ii) the p-values of standard t-tests of the separate null hypotheses that $\varphi_{h,0}^{j} = 0$ and $\varphi_{h,1}^{j} = 1$; (iii) the p-value from an F-test of the composite hypothesis that *simultaneously* $\varphi_{h,0}^{j} = 0$ and $\varphi_{h,1}^{j} = 1$.

Second, Pesaran and Timmermann (1992) propose a non-parametric market-timing (PT) test to investigate whether a model has economic value in forecasting the "direction" of asset price movements. In fact, one of the problems with the Mincer and Zarnowitz's test is that its small-sample properties heavily rely on parametric assumptions concerning $\xi_{t,t+h}^{j,\mu}$ and has only a weak connection to the practical uses of forecasts of stock and bond returns in financial markets. In particular, as discussed earlier, market traders may use forecasts not really to place bets based on the level of the forecast, but on their signs. The PT statistic overcomes these limitations and is based on computing $\hat{P}_h^{j,\mu}$, an estimate of the probability that r_{t+h}^j and its forecast $\hat{r}_{t,t+h}^{j,\mu}$ have the same sign "conditional" on independence of r_{t+h}^j from its forecast,

$$\hat{P}_h^{j,\mu} = \hat{P}_{r,h}^j \hat{P}_{\hat{r},h}^{j,\mu} + \left(1 - \hat{P}_{r,h}^j\right)\left(1 - \hat{P}_{\hat{r},h}^{j,\mu}\right),$$

where

$$\hat{P}_{r,h}^j \equiv \frac{1}{T-h}\sum_{t=1}^{T} I_{\{r_{t+h}^j>0\}} \text{ and } \hat{P}_{\hat{r},h}^{j,\mu} \equiv \frac{1}{T-h}\sum_{t=1}^{T} I_{\{\hat{r}_{t,t+h}^{j,\mu}>0\}}.$$

The PT statistic is then computed as

$$PT_h^{j,\mu} \equiv \frac{SR_h^{j,\mu} - \hat{P}_h^{j,\mu}}{\sqrt{\widehat{Var}\left(SR_h^{j,\mu}\right) - \widehat{Var}\left(\hat{P}_h^{j,\mu}\right)}} \overset{a}{\sim} N(0,1), \tag{18}$$

where $SR_h^{j,\mu}$ is the success ratio for model μ at horizon h.[7] Using its asymptotic distribution, the PT statistic is used to the null hypothesis that r_{t+h}^j and $\hat{r}_{t,t+h}^{j,\mu}$ are independently distributed. The connection to our goals in this paper comes from noting that when r_{t+h}^j and $\hat{r}_{t,t+h}^{j,\mu}$ are independently distributed, clearly model μ has no predictive power for the sign of r_{t+h}^j.

Third, we adopt Diebold and Mariano's (1995) equal predictive accuracy test. This allows the testing of whether two alternative forecasts $\mathcal{M}_1$ and $\mathcal{M}_2$ are statistically different. To derive the Diebold and Mariano (DM) statistic, we first compute the difference between the loss functions of two competing models (initially we consider a square loss function),[8]

$$diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2} \equiv L\left(e_{t,t+h}^{j,\mathcal{M}_1}\right) - L\left(e_{t,t+h}^{j,\mathcal{M}_2}\right) = \left(e_{t,t+h}^{j,\mathcal{M}_1}\right)^2 - \left(e_{t,t+h}^{j,\mathcal{M}_2}\right)^2, \tag{19}$$

with the DM statistic defined as

$$DM_{j,h}^{\mathcal{M}_1,\mathcal{M}_2} \equiv \frac{\frac{1}{T-h}\sum_{t=1}^{T} diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}}{\widehat{\sigma}\left(diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right)} \overset{a}{\sim} N(0,1). \tag{20}$$

The standard error of the loss differential is calculated using the standard Newey-West estimator.

van Dijk and Franses (2003, vDF) propose a weighted test of equal prediction accuracy. This modification of the DM test assigns more weight to extreme observations, therefore testing if a model is able to forecast outliers correctly. This may be of particular relevance in our case, predicting financial returns, given large returns are not only important for risk averse investors (who assign a higher marginal utility weight to losses than to gains) but also for regulatory purposes (e.g. value-at-risk and capital requirement issues). vDF propose the following three types of weighting functions, W_{it}, which effectively penalize forecasts errors

[7]In order to calculate the PT test statistic, all the observations for r_{t+h}^j and its forecasts $\hat{r}_{t,t+h}^{j,\mu}$ cannot have the same sign otherwise $\widehat{Var}\left(SR_h^{j,\mu}\right) = \widehat{Var}\left(\hat{P}_h^{j,\mu}\right)$ and the PT statistic is not defined.

[8]We also report results for an asymmetric (linex) loss function.

for extreme observations in both tails, left tail only,[9] and right tail only,

$$\begin{aligned}\text{(i) } W_{1t} &= 1-\phi(r_t^j)/\max\{\phi(r_t^j)\},\\ \text{(ii) } W_{2t} &= 1-\Phi(r_t^j),\\ \text{(iii) } W_{3t} &= \Phi(r_t^j),\end{aligned}$$

where $\phi(\cdot)$ is the probability density function of the forecast target variable, r_t^j, and $\Phi(\cdot)$ is the cumulative distribution function of the forecast target variable. In practise, the probability density function in the first weight is computed by applying a kernel smoothing method based on the normal kernel function while the empirical cumulative distribution function is used for the other weights. vDF suggest employing a standard Nadaraya-Watson kernel estimator to compute the $\phi(\cdot)$. As in vDF (2003), we employ all observations of the target variable in the whole sample period (1979:02-2007:01) to estimate $\phi(\cdot)$ and $\Phi(\cdot)$. Once a selection of a weighting function W_{it} is made, the DF statistics (sometimes also referred to as a modified, weighted-DM statistic, W-DM), is given by a simple weighted average loss differential of two competing models, $\mathcal{M}_1$ and $\mathcal{M}_2$, divided by its standard deviation,

$$DF_{j,h}^{\mathcal{M}_1,\mathcal{M}_2} \equiv \frac{\frac{1}{145-h}\sum_{t=1995:01}^{2007:01-h} W_t \times diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}}{\widehat{\sigma}\left(W_t \times diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}2}\right)}. \tag{21}$$

Here, the DF statistic is computed with a square loss function and the three different weighting functions as in van Dijk and Franses (2003). Similar to the DM statistic, the DF statistic has an asymptotic standard normal distribution under the usual assumption of forecasting errors. In particular, the following one-side tests are performed

$$H_0: E\left[W_t \times diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}2}\right] \leq 0,\ E\left[W_t \times diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}2}\right] \geq 0,$$

which in words means that model $\mathcal{M}_1$ outperforms (under-performs) model $\mathcal{M}_2$.

Finally, Giacomini and White (2006, henceforth GW) argue that standard out-sample predictive ability tests are not necessarily appropriate for real-time forecast methods. Given forecast errors are usually generated from parametric models that have to be recursively estimated over time, any differential loss function will be probably polluted by errors caused by estimation uncertainty concerning the parameters of the underlying models.[10] GW shift the focus from the unconditional mean of differences in loss functions (as in Equation (20)) across prediction models to the conditional expectation of such differences across forecast methods, i.e. from the null

$$H_o: E\left[diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right] = 0,$$

under true parameter values (i.e. probability limits of parameter estimates), to

$$H_o': E_{t-1}\left[diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right] = 0,$$

[9] In financial applications, overweighting the ability of a model to predict outliers in the left tail (large negative returns) may be particularly appealing.

[10] The Diebold and Mariano (1995) test was developed for the baseline case of no parameter uncertainty. Further, benchmarks such as the random walk model do not require estimation of any parameters. Another advantage of GW tests is that they may not suffer from biases when competing models are nested, see Corradi and Swanson (2007) and Golinelli and Parigi (2008).

under the estimated parameters of models $\mathcal{M}_1$ and $\mathcal{M}_2$. GW's approach delivers a few interesting payoffs, for instance conditional tests directly account for the effects of parameter uncertainty by expressing the null H_o' directly in terms of estimated parameters and fixed estimation windows.[11]

In the case $h = 1$ Giacomini and White (2006) exploit the fact that the null is equivalent to stating that $\{diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\}$ is a martingale difference sequence, implying that for all measurable functions g_t in the information set at time t it should be $E\left[g_t \cdot diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right] = 0$.[12] They show that given a set of q measurable functions $\mathbf{g}_t$, the null of equal conditional predictive ability (CPA) for a pair of models $\mathcal{M}_1, \mathcal{M}_2$ can be tested using the statistic

$$GW_{\mathbf{g}}^{\mathcal{M}_1,\mathcal{M}_2}(j,h) \equiv (T-h)\left[\frac{1}{T-h}\sum_{t=1}^{T}\mathbf{Z}_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h)\right]'\left[\hat{\mathbf{\Omega}}(Z_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h))\right]^{-1}\left[\frac{1}{T-h}\sum_{t=1}^{T}\mathbf{Z}_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h)\right], \tag{22}$$

where

$$\mathbf{Z}_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h) \equiv \mathbf{g}_t \cdot diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2} \qquad \hat{\mathbf{\Omega}}(Z_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h)) \equiv \sum_{i=-h}^{h}\widehat{Cov}\left[\mathbf{Z}_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h), \mathbf{Z}_{t+i}^{\mathcal{M}_1,\mathcal{M}_2}(j,h)\right].$$

Under regularity conditions, $GW_{\mathbf{g}}^{(m,n)}(j,h) \overset{a}{\sim} \chi^2_{(q)}$. The power properties of the tests obviously depend on the choice of test functions in $\mathbf{g}_t$, although it is also clear that rejections of H_o' with respect to some set of functions $\mathbf{g}_t$ may give indications as to ways in which the forecasting performance could be improved. As in Giacomini and White (2006), we set $\mathbf{g}_t \equiv [1\ \Delta diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}]'$ $(q = 2)$ and $\mathbf{g}_t \equiv [1\ \Delta dif_t^{(m,n,h)}\ \Delta dif_{t-1}^{(m,n,h)}$ $e_t^{(m,h)}\ e_{t-1}^{(m,h)}\ e_t^{(n,h)}\ e_{t-1}^{(n,h)}]'$, $(q = 7)$.

3.1. *The Pseudo Out-of-Sample Experiment*

We consider a recursive pseudo out-of-sample experiment. We recursively estimate the 25 models defined in Section 2 on an expanding window of data, starting from 1979:02-1995:01 and then proceeding to 1979:02-1995:02, 1979:02-1995:03, etc. up to the last possible available sample, 1979:02-2007:01. An initial sample of approximately 16 years of monthly observations guarantees the availability of a sufficient number of observations even in the presence of a large number of parameters to be estimated (up to 24 in the case of the MSH model). At each date we produce asset return forecasts for three alternative horizons, $h = 1$, 3 and 12 months. For instance, at the end of 1995:01 we compute forecasts for stock and bond returns for 1995:02, 1995:04, and 1996:01. This implies that for each combination of model, horizon, country, and asset-type one will produce $145 - h$ forecasts to be recorded and used for evaluation purposes (i.e., 144 for 1-month, 142 for 3-month and 133 for 12-month horizon forecasts). In the interests of brevity we report results for $h = 1$ and 12 months only, although complete results are available from the Authors upon request.

[11]Formally, GW test is not inconsistent with an expanding estimation window provided that a rule is set for to stop the process of window expansion before $T \to \infty$.

[12]In the case $h \geq 2$, $\{diff_{t,j,h}^{\mu_1,\mu_2}\}$ is not a martingale difference sequence but $\forall g_t$ in the information set, $\{g_t \cdot diff_{t,j,h}^{\mu_1,\mu_2}\}$ should be "finitely correlated", i.e. uncorrelated after a certain number of lags.

4. **Data**

We use monthly data on asset returns and a standard set of predictive variables sampled over the period 1979:02 - 2007:01. The data are obtained from Datastream and Global Financial Database. The series we collect are stock (r_t^{stock}) and bond (r_t^{bond}) returns, the log-dividend yield on equities (dy_t), changes in the short-term interest rate (3-month Treasury bill yields, Δi_t), the term spread ($Term_t$) defined as the difference between long- (10 year) and the short-term (3-month bill) government bond yields, the change in the effective log-exchange rate (Δs_t), the CPI inflation rate (π_t), changes in log-oil prices (Δoil_t), industrial production growth (ΔIP_t), and the change in the unemployment rate (Δu_t). Inflation, industrial production growth and the unemployment rates are seasonally adjusted using the X-11 adjustment procedure of Stock and Watson (2003). An Appendix provides details of the data sources, series construction and the series mnemonics.

Summary statistics for all the variables are presented in Table 1. In common with our understanding of financial asset returns, both stock and bond returns are characterised by a large standard deviation compared to their mean and significant non-normality (in particular excess kurtosis). Table 1 provides summary statistics for the data. Data on nominal stock and bond returns display typical features well-known in the literature. In annualized terms, mean stock returns are 14.3% with a volatility of 16.3%; mean bond returns are 9.9% with an annualized volatility of 5.2%. While the bond return series does exhibit significant autocorrelation in both levels and squares, the stock returns do not, which is not atypical when equity returns are sampled at a monthly frequency. With regard to the predictor variables, each exhibits varying degrees of non-normality. Again, with respect to the financial-based predictors (the change in the short-term rate and the term spread) these have a standard deviation larger than their mean. Noticeably, there is also large variability in our (monthly) measure of output. Finally, most of the predictor variables exhibit significant autocorrelation in both levels and squares. Moreover, this may lend some support to the view of Ferson and Harvey (1991) that asset returns predictability arises from predictability in the variables that form the information set, i.e. variables such as output and interest rates, which in part determine stock returns are themselves predictable.

5. **Out-of-Sample Results**

Table 2 presents an overview of the forecast results for one- and twelve-step ahead forecasting exercises. In particular, separately for stocks and bonds, it presents the "top three" models on the basis of the different forecast evaluation metrics of Section 3. This means that in correspondence to each metric and asset type we have ranked the 25 models introduced in Section 2 and in the table we now report the three best models in the ranking. With respect to stock returns, the Markov-switching models feature highly in the top two or three best models across nearly all forecast metrics and for both one-step ahead and twelve-step ahead forecasts. In particular, looking at the one-step ahead forecasts, the MS or MSH models rank in the top two at the one-step ahead forecast ten out of a possible twelve times. In contrast, the smooth-transition models only rank as high as third or fourth, while ARCH-based models rank also quite well, especially when combined within simple random walk benchmarks. Purely linear models only appear well down the rankings. In the case of stocks, out of 36 available "top three" spots in the ranking (3×6 forecast criteria $\times$ 2 horizons), MS or MSH appear 20 times. This is even more impressive than a 20/36 ratio, since it is clear that MS and MSH may at most occupy $2 \times 6 \times 2 = 24$ spots. To further stress how impressive this ranking performance is, notice that the next best model is a Logistic STR model with switching variable represented by the lagged T-bill rate, which appears 4 times out of a possible 12.

The qualitative findings in the case of prediction of bond returns are similar. The MS and MSH models again perform well, being ranked in the "top three" models another 20 times out of a possible 24. Differently from before, smooth-transition models only achieve a "top three" status 3 times (if one clusters together logistic and exponential STR models) and especially, ARCH models rank consistently in the middle and lower orders. The purely linear homoskedastic model and a homoskedastic random walk with drift perform quite well, ranking in the top three 4 times, while this count achieves 7 when the random walk is augmented to include ARCH terms. Interestingly, these ranking exercises fail to find any systematic differences across the rankings for predictive performances obtained for $h = 1$ and $h = 12$. Overall, these results overwhelmingly support the superiority of the non-linear models and the Markov-switching model in particular for forecasting UK stock and bond returns.

Table 3 presents the full set of results from which the summaries in Table 2 are distilled. Furthermore, this table also presents some additional forecast evaluations. Panel A reports the evaluations of the stock return forecasts for both $h = 1$ and 12. Panel B reports the same for bond returns. In particular, we present forecast accuracy assessments using the PT and MZ techniques. The PT test, as with the success ratio, focuses on forecasting the correct sign, and can be defined as a market-timing test. The MZ test is similar in spirit to mean squared error based metrics and measures whether the models provide unbiased forecasts and the extent to which they explain variation in actual returns. These results are again supportive of non-linear models, and of Markov switching models in particular. Looking at stock returns the MS and smooth-transition models notably perform well on the PT test for the one-step ahead forecasts, while these models also produce the highest R-squared values in the MZ test. Even though the linear models do perform reasonably well with regard to the individual coefficient results in the MZ test, suggesting that these models do provide unbiased forecasts even if they are not the most accurate. The results for bond returns are similar, with the Markov-switching models performing well on the basis of the PT test and the R-squared in the MZ test while the linear based models perform better in terms of the coefficient results of the MZ test though the joint hypothesis test strongly rejects the null in all cases. In fact, the MZ test leads to a rather negative assessment of the performance of all regime switching models, including TAR, STR, and Markov switching ones. These are all "rejected" in the sense that the null hypotheses of $\varphi^j_{h,0} = \varphi^j_{h,1} = 0$ are all rejected, both in individual and joint tests, and with p-values which are essentially nil. On the contrary, for bond returns it is especially the simplest models (such as AR(1), the random walk, and linear predictive regressions) that most easily "pass" the MZ tests, especially at the $h = 12$ horizon.

5.1. *Tests of Equal Predictive Accuracy*

Tables 2 and 3 report results under each of the 6 metrics described in Section 3 and additionally give results for the application of the Pesaran-Timmermann and Mincer-Zarnowitz tests to each of the 25 predictive models entertained in this paper (and in the earlier literature). However, as can be seen from these tables, according to a number of forecast metrics the differences in performance between the best models and the closest followers tends to be relatively small. For instance, it is doubtful whether the difference between the MAFE of the second best performing model under $h = 1$ for stock returns (MSH, with a mean of 2.58%) may be substantially superior to the third best model (a predictive regression with t-GARCH(1,1)-in mean effects, with a mean of 2.85%), especially in the light of the rather high monthly variance of UK stock returns, 4.71%. However, the information in Tables 2 and 3 affords no opportunity to statistically discriminate between these values. Therefore, Tables 4-6 present the various tests of equal predictive accuracy outlined in Section 3. Specifically, Table 4 reports Diebold-Mariano test statistics using both a squared (quadratic) loss function (above the diagonal) and an asymmetric linear exponential (linex) loss function (below the diagonal). Table 5 presents the GW test results for $q = 2$ above the diagonal and $q = 7$ below the diagonal. Finally, Table 6 reports the van Dijk-Franses (henceforth vDF) tests when the weighting functions are of types (ii) and (iii), i.e., $W_{2t} = 1 - \Phi(r_t^j)$ and $W_{3t} = \Phi(r_t^j)$, weighting either the left or the right tails of loss functions differences.[13]

Starting with Table 4, the entries above the main diagonal have to be read in the following way: when a model listed in a column significantly outperforms a model listed in the rows, the corresponding p-value will be small, ideally smaller than a 0.05 threshold. Such a small p-value indicates that the null of equal predictive accuracy under a given loss function, for a given asset return series, and at a given horizon can be rejected. The entries below the main diagonal have to be read as: when a model listed in a row significantly outperforms a model listed in a column (i.e., the null of equal predictive accuracy can be rejected), the corresponding p-value will be smaller than a 0.05 threshold. In the table, we have in fact boldfaced all p-values below or equal to 0.05. For instance, the boldfaced value of 0.004 on the top right corner of panel A ($h = 1$, stock return predictions) means that when the null of equal predictive accuracy for MSH and a simple, homoskedastic linear predictive regression is tested under a square loss function, the DM statistic yields a p-value of approximately 0.4%, which is highly statistically significant under all standard thresholds common to applied work.

Table 4 overwhelmingly shows that the Markov switching models consistently outperform all other models, both linear and non-linear. The exceptions are few and essentially simply that under a square loss function it may hard to tell apart the Markov switching models (for which however, the null of equal predictive accuracy cannot be rejected, when MS and MSH are compared) from the third model in the rankings of Table 2, the Logistic STR in which the T-bill rate is the transition variable. Table 4 also

[13]In these tables, to save space and favour readability, we have reported results for only 20 models excluding a few variations of the simple AR and random walk benchmarks that produced performances similar to their baseline versions.

stresses a key difference between the test results for forecasts of stock vs. bond returns. In the latter case, MS and MSH end up producing a statistically significant more accurate prediction performance than most other models for both the square and the linex loss functions, this is not the case for stock return forecasts, where the finding of diffuse rejections of the null hypotheses of equal predictive accuracy when the benchmark is either MS and MSH applies only under a square loss function but not under an asymmetric, linex loss. This may relate to the fact that stock returns have an asymmetric unconditional distribution and—even though Markov switching models are superior in point forecasts—the large forecast errors in the left tail that the left-skewness in stock returns may induce, ends up leading to a predictive performance that is not statistically different under a linex loss function. Finally, while there is abundant evidence that the Markov switching model provides a statistically significant forecast improvement over the alternate models, there is very limited evidence that the other non-linear models significantly outperform the linear models. This holds for both stock and bond returns, for both forecast horizons and under both the loss functions covered by Table 4.

Table 5 reports results of GW tests. In this case we have used only a square loss function, although results were qualitatively similar under a linex loss.[14] The table shows test results in the form of p-values, and for clarity we have once more boldfaced all p-values equal to or below 5%. Results above the main diagonal concern the case in which the set of instruments $\mathbf{g}_t \equiv [1 \ \Delta diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}]'$ is set to include only two lags of past changes in differences of loss functions ($q = 2$); results below the main diagonal concern the case of $q = 7$. The general tone of the implications of GW tests are similar to those from DM tests in Table 4: if there is any sign of sufficient evidence to reject the null of equal predictive accuracy, this evidence goes in favor of Markov switching models. However, we notice two major differences comparing Tables 4 and 5. First, and especially in the case of stock return predictions, when $q = 2$ and $h = 1$, there seems to be now some differences between MS and MSH, in the sense that while in most pair-wise comparisons most other models gave a recursive predictive performance that was inferior to the simpler MS model, this was not the case with respect to MSH.[15] Second, GW test (for both $q = 2$ and 7) signal the existence of substantial heterogeneity between short- and medium-term forecasting performances. For $h = 1$, it remains possible to tell apart a number of pairs of models, and the existence of sufficient evidence to reject the null of equal predictive accuracy seems to spread beyond the comparisons involving MS and MSH. This is especially obvious when the test is applied using long lags of past changes in loss function differentials, $q = 7$. On the contrary, for $h = 12$ there are very few pairs of models (cells) for which the null of equal predictive accuracy may be rejected. The GW evidence therefore weakens to some extent the DM evidence that the data contain sufficient evidence of heterogeneous recursive predictive performance at a 12-month horizon, when models seem instead to become very hard to tell apart.

[14]Detailed results are available from the Authors upon request. The number of cells containing p-values below a 0.05 threshold slightly diminishes when asymmetric loss functions are employed.

[15]However, even under $q = 2$ and a 1-month horizon, the null of equal predictive accuracy between MS and MSH could not be rejected with p-values of 0.53 and 0.64 for stocks and bonds, respectively.

Table 6 reports results of the vDF tests. As before, results are shown as p-values and values below or equal to 0.05 are boldfaced. Results above (below) the main diagonal concern the case in which the loss differentials are weighted to apply penalties only to losses in the left (right) tail of the empirical distribution of loss differences. Once more, we have used only a square loss function, although results were qualitatively similar under a linex loss.[16] Although the general qualitative tone of the results in the table are comparable to table 4, where standard DM tests were applied, two differences stand out. First, in the case of stock returns forecasts, when a weighting function that only considers loss differences in the left tail, it is clear that there is considerable more power to tell the models apart in terms of their predictive accuracy. Even without entering into much detail, it is clear that approximately half of the cells above the main diagonal of panels A and B of Table 6 are boldfaced, indicating that the null of equal predictive accuracy could not be rejected. However, in any case it remains the case that in all pair-wise tests, Markov switching models turn out to be superior to the remaining models, including nonlinear models of the STR and TAR types.[17] Yet it is interesting to see that under this weighting scheme, also nonlinear models such as Logistic STR models with GARCH(1,1) errors and TGARCH(1,1)-in mean augmented predictive regressions may often out-perform simple linear (often, homoskedastic) benchmarks when it comes to forecast stock returns at both $h = 1$ and 12. Second, under a weighting function that instead attaches weights only to loss differentials in the right tail, we notice an opposite effect, especially obvious at the short-end of the forecast horizons: for both stock and bond return short-term predictions, it becomes hard to reject the null of equal predictive accuracy for most pairs of models, including the Markov switching ones. All in all, Table 6 conveys the feeling that even when we weight standard DM tests to assign additional weight to either one of the tails of the loss differentials, the basic finding that regime switching models outperform simpler linear predictive regressions holds.

5.2. *Robustness Checks*

One simple criticism of our findings is that they may be highly sample specific, due to evaluating performance across the entire out-of-sample period. To counter this and by means of a robustness test on the preceding results we conduct a sub-sample exercise, where our sample is divided into three equal sub-samples – 1995:02-1999:01, 1999:02-2003:01 and 2003:02-2007:01 – and the above forecast exercise is separately repeated on each of these intervals.[18] Table 7 reports the predictive accuracy measures for stock and bond returns for horizons $h = 1$ and 12. These results largely confirm our full sample results, in that the Markov switching models outperform both the alternate non-linear and linear models over each of the samples and forecast metrics. However, Table 7 allows us to notice that the weak instability of predictive performance that the Markov switching models express, manifests itself in the following way: the third period (2003:02-2007:01)

[16] Detailed results are available from the Authors upon request. The number of cells containing p-values below a 0.05 threshold slightly diminishes when asymmetric loss functions are employed.

[17] This remark can also be extended to bond return forecasts, but only as far as $h = 1$ is concerned.

[18] For $h = 12$ the sub-samples are 1996:01-1999:09, 1999:10-2003:05 and 2003:06-2007:01.

is the one in which the distance between Markov switching models and the next best (nonlinear) models is maximum. For instance, during the third period, for $h = 1$ MSH lowers the RMSFE vs. the best of the non-Markov switching model (in this case, a t-GARCH(1,1)-in mean predictive regression) by 14%, the MAFE by 8.4%, and increases the success ratio by 6.3%. On the contrary, the first sub-period (1995:02-1999:01) is characterized by a good performance by the Markov switching models, that however fail to be classified as "best" models according to the majority of the criteria. During the second sub-period (1999:02-2003:01) the MS and MSH are systematically the more accurate models, but the distance from other strong nonlinear competitors (such as a Logistic STR model with switching variable driven by one lag of the 1-month T-bill) tends to be modest, for instance 4.2% according to RMSFE, 4.3% by MAFE, and an increase of 8.3% in the success ratio.[19] We also repeat the DM, GW and DF tests over sub-periods, at least for the case of $h = 1$. Again the findings are consistent across the sub-periods and supportive of our full sample analysis.[20]

A further criticism of the methods adopted here is that the distribution of the Diebold-Mariano may be unknown in the presence of nested models. McCracken (2007) introduces a test statistic to compare two nested models for one-step ahead predictive horizons, comparable to the DM statistic that applies to non-linear models. We find our results are robust to accounting for nesting effects on the asymptotic distribution of the DM statistic. The MS and MSH models remain significantly more accurate than all the models they nest (i.e., linear models, random walk and AR(1)).

Finally to alleviate any concern that the van Dijk and Franses (2003) test statistics reported in Table 6 have employed strongly asymmetric weighting functions over either the left or right tail forecasts (loss functions differences), we provide robust evidence that are findings are not unduly influenced by this assumption. Table 8 reports the vDF tests under an additional weighting scheme which places extra weight on both the left and right tails, i.e., when the weighting function $W_{1t} = 1 - \phi(r_t^j)/\max\{\phi(r_t^j)\}$ is applied. In this case, to save space, we report results for $h = 1$ above the main diagonal and results for $h = 12$ below the diagonal. The results are largely consistent with those reported in Table 6: the Markov switching models are superior to virtually all other models. However, differently from Table 6 (panels A and B), in Table 8 (panel A) we notice that when stock returns are the target of prediction, applying a weighting function that over-weights loss differentials in the tails tends to greatly increase our ability to distinguish the predictive accuracy of alternative models, in the sense that the null of equal accuracy may be rejected for more than half of all possible pairs (and more, if one focusses on the lower, $h = 12$ panel). In particular, MS and MSH turn out to be superior to most of the alternative nonlinear models when loss differences that correspond to returns in the tails are adequately over-weighted. This may be one additional lesson: Markov switching models are most useful—in the sense that they are easier to tell apart from both simple benchmarks and other regime switching frameworks—when performance in both tails is of primary concern.[21]

[19] Interestingly, the superior predictive performance of MS and MSH tends to be more uniform at a $h = 12$ horizon.

[20] Results available from the authors on request.

[21] However, this interesting finding hardly applies to bond return predictions. Given the obvious differences between typical dynamics and time series properties of stock and bond returns, it remains to be seen whether this apparent correspondence between tail thickness and performance potential of Markov switching models extends beyond the UK data we have employed

6. **Conclusions**

In this paper we provide a comprehensive examination of the comparative predictive performance of linear and non-linear models for U.K. asset returns. In addition to basic linear models and standard autoregressive benchmarks we consider GARCH and EGARCH models and allow for ARCH-in-mean effects in the conditional mean. With respect to non-linear models we examine threshold, smooth transition and Markov switching models. The evidence in the prior literature is somewhat piecemeal, only considering subsets of these models, only stocks or bonds but rarely both, and a much smaller range of evaluation metrics and accuracy tests. Consequently it fails to provide a consistent message as to which models produce the most accurate forecasts of U.K. asset returns.

Our results provide a clear picture: that capturing non-linear effects in U.K. asset returns is important. Moreover, the best predictive performance comes from Markov switching models. Not only is the predictive performance of this class of models relatively better, it is also statistically significantly better. This finding is particularly strong (i.e., uniformly obtained across different sample periods, different metrics, and alternative statistical tests of equal predictive accuracy) for short-term forecasts, especially of bond returns. Our results show that independent of the chosen evaluation metric, predictive accuracy test, choice of sample period or loss function Markov switching models consistently out-perform all other models.

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Data Appendix

Variable	Source	Mnemonic
Stock Return 100*[ln(p_t)-ln(p_{t-1})]	Total Market Index, Datastream	TOTMKUK(RI)
Bond Return 100*[ln(p_t)-ln(p_{t-1})]	Total Bond Return Index, Global Financial Database	TRGBRGVM
Dividend Yield $\ln\left(\frac{DY_t}{100}\right)$	Total Market Index, Datastream	TOTMKUK(DY)
Change in Short-term interest rate tb_t - tb_{t-1}	3 Month Treasury Bill (tb), Global Financial Database	ITGBR3D
Term Spread gb_t - tb_t	10 Year Government Bond (gb), Datastream	UKI61...
Inflation 100*[ln(p_t)-ln(p_{t-1})]	Consumer Price Index, Datastream Seasonally adjusted using Stock and Watson (2003) procedure.	UKI64...F
Industrial Production 100*[ln(p_t)-ln(p_{t-1})]	Industrial Production, Datastream Seasonally adjusted using Stock and Watson (2003) procedure.	UKI66..IG
Exchange Rate 100*[ln(p_t)-ln(p_{t-1})]	Nominal Effective Trade Weighted Exchange Rate, Datastream	UKI..NEUE
Change in Unemployment Rate un_t - un_{t-1}	Unemployment rate (seasonally adjusted), Global Financial Database	UNGBRM
Change in Oil Prices 100*[ln(p_t)-ln(p_{t-1})]	World Crude Petroleum Price, Datastream	WDI76AADF

Table 1

Summary Statistics for Stock and Bond Returns vs. Prediction Variables

The table reports a few summary statistics for monthly stock and long-term government bond return series, and the macroeconomic variables employed as predictors of asset returns. The sample period is 1979:02 – 2007:01. All returns are expressed in percentage terms. LB(j) denotes the j-th order Ljung-Box statistic. * denotes 5% significance, ** significance at 1%.

Series	Mean	Median	St. Dev.	Skewness	Kurtosis	Jarque-Bera	LB(4)	LB(4)-squares
	Asset Returns							
Stock return	1.1885	1.8163	4.7071	-1.3903	10.0568	805.42**	3.0887	2.2550
Bond return	0.8219	0.7790	1.4906	0.3709	5.1326	71.379**	23.056**	12.326*
	Prediction Variables							
Log dividend yield	-3.2265	-3.2176	0.2583	-0.1225	2.2477	8.7639*	1225.5**	1227.7**
Δ 3month T-bill yield	-0.0208	-0.0106	0.5767	1.1832	9.9019	745.30**	1.1626	45.915**
Term spread	0.0534	-0.0500	1.6873	-0.3806	2.9551	8.1409*	1079.5**	939.66**
CPI inflation rate	0.3809	0.2963	0.3208	1.0395	3.9821	74.016**	465.94**	587.23**
Industrial prod. growth	0.9869	1.4647	12.0630	-0.3860	4.1650	27.348**	16.913**	19.932**
Δ log eff. exchange rate	0.0134	0.0370	1.6592	-0.3874	5.4494	92.396**	31.939**	23.009**
Δ unemployment rate	0.0033	0.0000	0.1196	0.6786	4.5150	57.918**	428.92**	176.67**

Table 2

Overview of Forecasting Performance: Best Three Predictive Models According to Alternative Criteria

Criterion	Horizon	Stocks	Bonds
RMSFE	h=1	1. MS	1. MS
		2. MSH	2. MSH
		3. Logistic STAR - T-bill	3. Random walk with drift
	h=12	1. MS	1. MS
		2. MSH	2. MSH
		3. Logistic STAR - T-bill	3. RW w/drift & GARCH(1,1)-in mean
Bias	h=1	1. RW w/drift & TARCH(1,1)-in mean	1. MS
		2. RW w/drift & t-TARCH(1,1)-in mean	2. MSH
		3. RW w/drift & GARCH(1,1)-in mean	3. RW w/drift & GARCH(1,1)-in mean
	h=12	1. Linear homoskedastic	1. TAR-SRF
		2. RW w/drift & GARCH(1,1)-in mean	2. Logistic STAR -T-bill
		3. MS	3. MS
Forecast Variance	h=1	1. MSH	1. MS
		2. MS	2. MSH
		3. Logistic STAR - T-bill	3. Random walk with drift
	h=12	1. MSH	1. MSH
		2. MS	2. MS
		3. Logistic STAR -T-bill	3. AR(1)
MAFE	h=1	1. MS	1. MS
		2. MSH	2. MSH
		3. RW w/drift & t-GARCH(1,1)-in mean	3. AR(1)
	h=12	1. MS	1. MS
		2. MSH	2. MSH
		3. Random walk with drift	3. Linear homoskedastic
MPFE	h=1	1. MSH	1. AR(1) w/GARCH(1,1)-in mean
		2. MS	2. MS
		3. RW w/drift & EGARCH(1,1)-in mean	3. RW w/drift & t-GARCH(1,1)-in mean
	h=12	1. RW w/drift & t-TARCH(1,1)-in mean	1. Exponential STAR - T-bill
		2. MS	2. TAR-SRF
		3. Linear Homoskedastic	3. Logistic STAR - T-bill
Success Ratio	h=1	1. MSH	1. MSH
		2. MS	2. MS
		3. Random walk with drift	3. Random walk with drift
	h=12	1. MS	1. Random walk with drift
		2. MSH	2. MSH
		3. Random walk with drift	3. MS

Table 3

Predictive Accuracy Measures for Stock and Bond Returns

Panel A: Stock Returns

Measure	RMSFE		Bias		Forecast Variance		MAFE		MPFE		Success Ratio		PT		MZ regression (R-square)		MZ (p-value for intercept = 0)		MZ (p-value for coefficient = 1)		MZ (p-value for intercept =0 and coefficient =1)	
Model	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12
Linear	4.001	4.263	0.846	**0.066**	15.294	18.170	3.105	3.186	1.162	**0.733**	0.514	0.549	0.565	-0.988	0.035	0.017	0.011	0.011	**0.697**	0.000	0.036	0.001
Random walk (with drift)	4.015	4.140	-0.515	-0.626	15.857	16.749	2.936	**3.020**	1.186	1.232	**0.653**	**0.647**	N.A.	N.A.	0.000	0.002	**0.756**	**0.465**	**0.632**	**0.353**	**0.275**	**0.142**
AR(1)	4.024	4.191	-0.503	-0.661	15.937	17.130	2.948	3.043	1.185	1.221	0.653	0.647	N.A.	N.A.	0.002	0.021	**0.368**	0.037	**0.262**	0.012	**0.174**	0.008
Random walk (with drift and GARCH(1,1))	4.012	4.141	-0.460	-0.586	15.881	16.800	2.936	3.028	1.156	1.225	0.653	0.647	N.A.	N.A.	0.000	0.004	**0.625**	**0.321**	**0.494**	**0.218**	**0.310**	**0.124**
AR(1) with GARCH(1,1)	4.024	4.156	-0.451	-0.581	15.993	16.934	2.941	3.035	1.188	1.219	0.653	0.647	N.A.	N.A.	0.004	0.004	**0.232**	**0.237**	**0.150**	**0.109**	**0.145**	**0.076**
GARCH(1,1) in mean and exogenous predictors	4.271	4.268	1.078	**0.108**	17.077	18.206	3.246	3.207	1.743	0.793	0.514	0.564	0.565	-0.278	0.005	0.011	0.011	0.018	0.001	0.000	0.000	0.001
GARCH(1,1)-in mean and exogenous predictors - t dist.	3.889	4.273	**-0.208**	-0.272	15.083	18.188	**2.847**	3.171	1.332	0.844	0.653	0.602	1.547	-0.560	0.047	0.012	**0.740**	0.022	**0.906**	0.000	**0.810**	0.001
EGARCH(1,1)-in mean and exogenous predictors	4.076	4.822	0.266	0.317	16.545	23.154	3.107	3.475	**1.071**	0.964	0.535	0.541	0.075	-0.449	0.009	0.004	**0.069**	0.031	0.006	0.000	0.018	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	3.959	4.881	-0.341	0.331	15.556	23.710	2.922	3.499	1.430	1.135	0.611	0.564	-0.132	0.312	0.025	0.000	**0.900**	0.043	**0.311**	0.000	**0.353**	0.000
TGARCH(1,1)-in mean and exogenous predictors	4.102	4.361	**-0.016**	0.172	16.824	18.986	3.034	3.309	1.475	0.753	0.542	0.511	-1.310	-1.377	0.003	0.031	**0.096**	0.005	0.003	0.000	0.011	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	3.940	4.294	**0.017**	-0.141	15.523	18.415	2.934	3.185	1.482	**0.670**	0.583	0.579	0.320	-0.707	0.030	0.010	**0.441**	0.023	**0.219**	0.000	**0.468**	0.001
Exponential STAR - T-bill	3.928	4.102	0.845	1.018	14.713	15.787	3.055	3.212	1.209	1.339	0.569	0.526	**1.751**	1.152	**0.071**	0.054	0.010	0.007	**0.919**	**0.688**	0.034	0.014
Exponential STAR-SRF	4.023	4.262	0.768	0.933	15.591	17.297	3.083	3.314	1.448	1.291	0.569	0.534	**1.751**	0.737	0.037	0.028	0.017	0.022	**0.074**	0.004	0.014	0.001
Logistic STAR - T-bill	**3.811**	**3.970**	0.317	0.791	**14.425**	**15.135**	2.859	3.058	1.237	1.596	0.632	0.549	**2.303**	0.995	0.103	**0.116**	**0.171**	0.022	**0.138**	**0.061**	**0.203**	0.012
Logistic STAR-SRF	4.004	4.247	0.888	1.164	15.241	16.686	3.089	3.300	1.106	1.264	0.542	0.504	1.488	1.000	0.040	0.028	0.009	0.011	**0.534**	0.050	0.023	0.001
TAR-SR	4.094	4.234	0.749	0.854	16.202	17.201	3.171	3.302	1.482	1.625	0.535	0.519	0.822	0.803	0.009	0.009	0.018	0.031	0.034	0.022	0.009	0.005
TAR-SRF	4.143	4.250	0.614	0.671	16.791	17.612	3.251	3.356	1.150	1.163	0.528	0.534	0.916	1.279	0.014	0.023	0.025	0.044	0.001	0.001	0.001	0.001
Logistic STAR-GARCH(1,1)	4.081	4.608	0.752	1.975	16.090	17.331	3.133	3.679	1.210	1.005	0.542	0.466	1.158	**1.781**	0.007	0.016	0.018	0.013	**0.068**	0.008	0.016	0.000
MS Two-state homoskedastic	**3.376**	**3.371**	0.424	**-0.110**	**11.217**	**11.351**	**2.506**	**2.512**	**1.035**	**0.704**	**0.757**	**0.759**	**5.430**	**5.164**	**0.364**	**0.451**	**0.708**	0.001	0.000	0.000	0.000	0.000
MS Two-state heteroskedastic	**3.543**	**3.380**	0.437	-0.484	**12.360**	**11.191**	**2.576**	**2.541**	**0.856**	0.790	**0.771**	**0.744**	**5.855**	**4.721**	**0.225**	**0.404**	**0.226**	0.000	**0.329**	0.000	**0.209**	0.000

Panel B: Bond Returns

Measure	RMSFE		Bias		Forecast Variance		MAFE		MPFE		Success Ratio		PT		MZ regression (R-square)		MZ (p-value for intercept = 0)		MZ (p-value for coefficient = 1)		MZ (p-value for intercept =0 and coefficient =1)	
Model	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12	h=1	h=12
Linear	1.265	1.275	0.122	-0.197	1.584	1.586	0.969	**0.973**	0.384	-0.962	0.674	**0.707**	0.697	N.A.	0.000	0.006	0.000	0.013	0.000	0.001	0.000	0.001
Random walk (with drift)	**1.230**	1.271	-0.340	-0.392	**1.397**	1.462	0.949	0.989	-1.038	-1.507	**0.715**	0.707	N.A.	N.A.	0.021	0.014	**0.158**	**0.283**	**0.221**	**0.379**	0.002	0.001
AR(1)	1.235	1.270	-0.250	-0.405	1.462	**1.450**	**0.943**	0.985	0.215	-1.552	0.708	0.707	-0.633	N.A.	0.006	**0.030**	**0.187**	**0.109**	0.016	**0.183**	0.003	0.000
Random walk (with drift and GARCH(1,1))	1.232	**1.248**	-0.271	-0.284	1.445	1.478	0.951	0.979	-1.017	-1.308	0.715	0.707	N.A.	N.A.	**0.031**	0.003	0.010	**0.728**	0.006	**0.395**	0.001	0.021
AR(1) with GARCH(1,1)	1.238	1.253	-0.201	-0.296	1.493	1.483	0.941	0.986	**0.013**	-1.403	0.715	0.707	N.A.	N.A.	0.000	0.003	**0.054**	**0.629**	0.005	**0.280**	0.003	0.013
GARCH(1,1) in mean and exogenous predictors	1.258	1.300	**0.037**	-0.154	1.580	1.667	0.955	0.995	0.169	-0.871	0.667	0.699	-0.164	0.154	0.000	0.008	0.001	0.002	0.000	0.000	0.000	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	1.253	1.294	0.078	-0.158	1.565	1.649	0.955	0.993	**0.102**	-0.907	0.674	0.684	0.009	-1.129	0.000	0.006	0.000	0.003	0.000	0.000	0.001	0.000
EGARCH(1,1)-in mean and exogenous predictors	1.254	1.291	0.054	-0.108	1.570	1.656	0.951	0.993	0.121	-0.758	0.674	0.669	0.261	-0.898	0.001	0.002	0.001	0.003	0.000	0.000	0.000	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	1.253	1.282	0.094	-0.107	1.562	1.631	0.956	0.983	0.403	-0.661	0.667	0.669	0.091	-0.898	0.000	0.001	0.000	0.006	0.000	0.000	0.001	0.001
TGARCH(1,1)-in mean and exogenous predictors	1.257	1.299	0.044	-0.141	1.578	1.667	0.956	0.990	0.150	-0.855	0.681	0.707	0.192	0.647	0.000	0.009	0.001	0.001	0.000	0.000	0.000	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	1.251	1.304	0.093	-0.156	1.556	1.675	0.955	0.998	0.179	-0.881	0.674	0.707	0.261	0.647	0.001	0.011	0.001	0.001	0.000	0.000	0.001	0.000
Exponential STAR - T-bill	1.393	1.472	0.235	0.251	1.886	2.103	1.030	1.086	0.140	**-0.073**	0.667	0.624	0.534	-0.375	0.014	0.004	0.000	0.000	0.000	0.000	0.000	0.000
Exponential STAR-SRF	1.274	1.314	0.142	0.132	1.602	1.708	0.978	1.013	0.521	0.389	0.632	0.624	-0.413	-0.375	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
Logistic STAR - T-bill	1.276	1.299	0.085	**0.049**	1.620	1.685	0.980	1.001	0.657	**0.355**	0.646	0.647	0.287	0.281	0.001	0.000	0.000	0.001	0.000	0.000	0.000	0.000
Logistic STAR-SRF	1.274	1.314	0.142	0.132	1.602	1.708	0.978	1.013	0.521	0.389	0.632	0.624	-0.413	-0.375	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
TAR-SR	1.287	1.341	0.104	0.094	1.646	1.790	0.992	1.040	0.996	0.761	0.604	0.564	**-1.676**	**-2.112**	0.001	0.011	0.000	0.000	0.000	0.000	0.000	0.000
TAR-SRF	1.276	1.306	0.039	**0.006**	1.626	1.705	1.009	1.040	0.345	**0.196**	0.646	0.632	-0.628	-0.712	0.003	0.001	0.000	0.001	0.000	0.000	0.000	0.000
Logistic STAR-GARCH(1,1)	1.264	1.302	0.113	0.094	1.585	1.687	0.968	0.999	0.587	0.453	0.639	0.639	-0.277	0.129	0.001	0.000	0.000	0.000	0.000	0.000	0.000	0.000
MS Two-state homoskedastic	**1.014**	**1.032**	**-0.013**	**-0.090**	**1.028**	**1.058**	**0.776**	**0.779**	**-0.095**	-0.394	**0.771**	**0.722**	**4.614**	**2.057**	**0.348**	**0.430**	0.001	0.000	0.000	0.000	0.000	0.000
MS Two-state heteroskedastic	**1.019**	**1.033**	**0.020**	-0.124	**1.038**	**1.052**	**0.787**	**0.779**	-0.175	-0.501	**0.757**	**0.714**	**3.808**	1.437	**0.323**	**0.468**	0.007	0.000	0.001	0.000	0.003	0.000

Note: In the RMSFE, Bias, FV, MAFE, SR, and MZ R^2 columns, we boldface the best three statistics returned across all models. In the PT column and in the columns concerning statistical tests on coefficients of the Mincer-Zarnowitz regression, we boldfaced p-values which are equal or above a threshold of 5%, indicating that the null of α=0 and β=1 cannot be rejected with a high level of confidence.

Table 4

Diebold-Mariano Equal Predictive Accuracy Tests: Stock Return Forecasts, Square vs. Linex Loss Functions

Panel A: 1-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.543	0.569	0.532	0.568	0.975	0.122	0.754	0.354	0.810	0.243	0.124	0.577	0.192	0.545	0.948	0.926	0.953	**0.000**	**0.004**
Random walk (with drift)	**0.019**		0.837	0.286	0.723	0.871	**0.043**	0.744	0.210	0.823	0.197	0.310	0.517	0.178	0.468	0.796	0.748	0.709	**0.000**	**0.011**
AR(1)	**0.009**	0.845		0.122	0.514	0.863	**0.037**	0.711	0.182	0.794	0.176	0.290	0.497	0.167	0.444	0.772	0.736	0.687	**0.000**	**0.008**
Random walk (with drift and GARCH(1,1))	**0.009**	0.865	0.166		0.815	0.876	**0.046**	0.758	0.232	0.836	0.207	0.315	0.525	0.184	0.478	0.817	0.756	0.722	**0.000**	**0.011**
AR(1) with GARCH(1,1)	**0.015**	0.885	0.164	0.156		0.863	**0.037**	0.708	0.188	0.800	0.178	0.297	0.496	0.174	0.444	0.767	0.730	0.676	**0.000**	**0.011**
GARCH (1,1) in mean and exogenous predictors	0.919	0.928	0.932	0.929	0.928		**0.024**	0.162	0.062	0.171	0.027	**0.009**	0.072	0.052	**0.023**	0.128	0.202	0.104	**0.000**	**0.002**
GARCH (1,1) in mean and exogenous predictors - t dist.	0.092	0.171	0.166	0.166	0.167	0.083		0.993	0.911	0.999	0.789	0.607	0.811	0.368	0.853	1.000	0.947	0.976	**0.001**	0.059
EGARCH (1,1) in mean and exogenous predictors	0.127	0.251	0.219	0.234	0.240	0.089	0.999		0.026	0.633	**0.014**	0.159	0.358	0.115	0.275	0.571	0.657	0.517	**0.000**	**0.010**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.087	0.173	0.167	0.168	0.169	0.082	0.842	0.149		0.975	0.356	0.421	0.657	0.241	0.637	0.923	0.859	0.878	**0.000**	**0.030**
TGARCH (1,1) in mean and exogenous predictors	0.084	0.970	0.425	0.800	0.919	0.080	0.896	0.843	0.903		**0.003**	0.139	0.303	0.128	0.216	0.466	0.595	0.430	**0.000**	**0.007**
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.109	0.224	0.200	0.210	0.215	0.085	0.984	0.417	0.963	0.131		0.463	0.730	0.272	0.735	0.971	0.912	0.949	**0.000**	**0.031**
Exponential STAR - TBILL	0.899	0.946	0.971	0.953	0.949	0.079	0.905	0.882	0.908	0.909	0.894		0.735	0.301	0.889	0.936	0.993	0.978	**0.000**	**0.016**
Exponential STAR - SRF	0.227	0.432	0.343	0.391	0.409	0.102	0.993	0.932	0.954	0.319	0.929	0.178		0.187	0.432	0.719	0.780	0.669	**0.000**	**0.013**
Logistic STAR - TBILL	0.106	0.210	0.192	0.199	0.203	0.085	0.940	0.280	0.719	0.125	0.282	0.104	0.057		0.801	0.883	0.937	0.924	**0.037**	0.157
Logistic STAR - SRF	0.967	0.981	0.994	0.989	0.985	0.082	0.915	0.883	0.920	0.931	0.900	0.122	0.794	0.903		0.920	0.924	0.897	**0.000**	**0.005**
TAR - Tbill	0.843	0.900	0.913	0.902	0.901	0.064	0.879	0.858	0.880	0.866	0.868	0.771	0.810	0.870	0.826		0.648	0.426	**0.000**	**0.002**
TAR - SRF	0.901	0.943	0.965	0.948	0.945	0.078	0.906	0.885	0.909	0.911	0.896	0.891	0.831	0.898	0.885	0.295		0.279	**0.000**	**0.002**
Logistic STAR - GARCH	0.842	0.919	0.941	0.924	0.920	0.071	0.886	0.862	0.888	0.875	0.873	0.514	0.801	0.876	0.813	0.156	0.084		**0.000**	**0.001**
MS Two-state Homoskedastic	0.499	0.851	0.682	0.797	0.825	0.106	0.936	0.902	0.936	0.737	0.915	0.281	0.796	0.921	0.444	0.250	0.250	0.297		0.871
MS Two-state Heteroskedastic	0.842	0.844	0.844	0.844	0.844	0.835	0.844	0.843	0.844	0.843	0.843	0.842	0.841	0.843	0.842	0.842	0.841	0.842	0.841	

Panel B: 12-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		**0.011**	0.180	**0.008**	0.052	0.584	0.578	0.962	0.955	1.000	0.726	0.220	0.498	0.107	0.472	0.413	0.477	0.856	**0.001**	**0.000**
Random walk (with drift)	0.115		0.926	0.527	0.861	1.000	1.000	0.985	0.972	1.000	1.000	0.439	0.735	0.259	0.653	0.747	0.669	0.904	**0.009**	**0.004**
AR(1)	0.117	0.132		0.098	0.098	0.872	0.996	0.980	0.956	0.991	0.969	0.374	0.622	0.211	0.576	0.605	0.583	0.865	**0.011**	**0.005**
Random walk (with drift and GARCH(1,1))	0.116	0.957	0.872		0.783	1.000	1.000	0.986	0.973	1.000	1.000	0.438	0.736	0.257	0.654	0.747	0.670	0.905	**0.008**	**0.004**
AR(1) with GARCH(1,1)	0.116	0.125	0.000	0.122		0.989	1.000	0.982	0.965	1.000	1.000	0.416	0.695	0.234	0.631	0.710	0.642	0.894	**0.009**	**0.004**
GARCH (1,1) in mean and exogenous predictors	0.842	0.882	0.881	0.882	0.881		0.547	0.963	0.957	1.000	0.723	0.204	0.486	0.081	0.463	0.384	0.467	0.850	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors - t dist.	0.099	0.881	0.880	0.881	0.880	0.115		0.970	0.948	0.988	0.753	0.242	0.478	0.119	0.461	0.393	0.464	0.833	**0.002**	**0.001**
EGARCH (1,1) in mean and exogenous predictors	0.896	0.900	0.901	0.900	0.901	0.896	0.897		0.562	0.069	0.036	**0.041**	0.068	**0.016**	0.077	**0.040**	0.081	0.304	**0.002**	**0.001**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.891	0.894	0.894	0.894	0.894	0.891	0.892	0.662		0.075	0.056	**0.019**	**0.038**	**0.012**	0.061	**0.046**	**0.037**	0.268	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors	0.882	0.884	0.883	0.884	0.883	0.894	0.890	0.105	0.109		**0.029**	0.123	0.296	**0.048**	0.316	0.180	0.318	0.770	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.877	0.882	0.881	0.882	0.882	0.883	0.884	0.106	0.110	0.870		0.198	0.436	0.088	0.423	0.335	0.430	0.836	**0.001**	**0.000**
Exponential STAR - TBILL	0.154	0.967	0.951	0.967	0.952	0.154	0.171	0.101	0.107	0.144	0.141		1.000	0.224	0.994	0.804	0.988	0.992	**0.000**	**0.000**
Exponential STAR - SRF	0.119	0.944	0.916	0.944	0.917	0.124	0.125	0.101	0.107	0.120	0.122	1.000		0.050	0.446	0.404	0.334	0.947	**0.000**	**0.000**
Logistic STAR - TBILL	0.168	0.805	0.978	0.794	0.979	0.167	0.184	0.100	0.107	0.156	0.152	0.223	0.209		0.977	0.957	0.956	0.973	**0.000**	**0.001**
Logistic STAR - SRF	0.360	0.890	0.888	0.890	0.888	0.280	0.793	0.103	0.109	0.166	0.136	0.865	0.865	0.855		0.467	0.507	0.999	**0.000**	**0.000**
TAR - Tbill	0.141	0.975	0.950	0.974	0.951	0.142	0.152	0.100	0.107	0.135	0.134	0.055	0.085	0.639	0.127		0.542	0.885	**0.000**	**0.000**
TAR - SRF	0.137	0.932	0.918	0.932	0.919	0.139	0.151	0.101	0.107	0.132	0.131	0.704	1.000	0.753	0.138	0.844		0.930	**0.000**	**0.000**
Logistic STAR - GARCH	0.900	0.896	0.895	0.896	0.895	0.902	0.901	0.108	0.111	0.901	0.909	0.884	0.891	0.878	0.914	0.887	0.888		**0.001**	**0.001**
MS Two-state Homoskedastic	0.118	0.131	0.131	0.129	0.139	0.120	0.121	0.099	0.106	0.118	0.119	0.059	0.092	**0.014**	0.113	0.063	0.089	0.106		0.542
MS Two-state Heteroskedastic	0.115	0.108	0.050	0.107	0.060	0.117	0.118	0.099	0.106	0.115	0.117	**0.048**	0.080	**0.014**	0.109	**0.048**	0.079	0.104	0.791	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) test of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values under a symmetric, square loss function; below the main diagonal, in each cell we show DM p-values obtained under an asymmetric linex loss function.

Table 4 [continued]

Diebold-Mariano Equal Predictive Accuracy Tests: Bond Return Forecasts, Square vs. Linex Loss Functions

Panel C: 1-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.212	0.153	0.212	0.165	0.276	0.092	0.215	0.188	0.264	0.084	0.946	0.856	0.674	0.856	0.824	0.649	0.472	**0.000**	**0.000**
Random walk (with drift)	**0.012**		0.579	0.657	0.634	0.764	0.725	0.733	0.721	0.753	0.696	0.976	0.838	0.813	0.838	0.899	0.834	0.789	**0.000**	**0.000**
AR(1)	**0.013**	0.971	0.000	0.455	0.707	0.813	0.763	0.762	0.748	0.793	0.718	0.973	0.889	0.867	0.889	0.930	0.855	0.844	**0.000**	**0.000**
Random walk (with drift and GARCH(1,1))	**0.013**	0.986	0.060	0.000	0.608	0.761	0.720	0.725	0.713	0.750	0.688	0.976	0.840	0.810	0.840	0.903	0.830	0.787	**0.000**	**0.000**
AR(1) with GARCH(1,1)	**0.006**	0.952	0.890	0.933	0.000	0.795	0.737	0.735	0.717	0.775	0.686	0.972	0.882	0.854	0.882	0.931	0.841	0.832	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors	0.022	0.988	0.987	0.987	0.995	0.000	0.277	0.315	0.352	0.455	0.199	0.957	0.934	0.762	0.934	0.877	0.734	0.794	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors - t dist.	0.074	0.992	0.993	0.992	0.997	0.997	0.000	0.531	0.498	0.699	0.317	0.960	0.973	0.794	0.973	0.893	0.777	0.866	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors	**0.033**	0.987	0.987	0.985	0.996	0.559	0.109	0.000	0.461	0.675	0.343	0.960	0.970	0.816	0.970	0.890	0.768	0.880	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.085	0.993	0.994	0.992	0.999	0.952	0.318	0.917	0.000	0.639	0.371	0.962	0.955	0.804	0.955	0.884	0.773	0.828	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors	**0.012**	0.983	0.980	0.981	0.991	0.712	0.103	0.633	0.232	0.000	0.200	0.957	0.959	0.774	0.959	0.879	0.732	0.846	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.061	0.991	0.992	0.991	0.997	0.996	0.265	0.890	0.556	0.877	0.000	0.963	0.989	0.828	0.989	0.908	0.804	0.933	**0.000**	**0.000**
Exponential STAR - TBILL	0.902	0.946	0.937	0.943	0.932	0.915	0.911	0.915	0.912	0.914	0.912	0.000	0.069	0.081	0.069	0.101	0.094	0.055	**0.000**	**0.000**
Exponential STAR - SRF	0.888	0.989	0.989	0.989	0.995	0.989	0.958	0.985	0.952	0.996	0.968	0.100	0.000	0.531	0.328	0.711	0.528	0.052	**0.000**	**0.000**
Logistic STAR - TBILL	0.634	0.980	0.978	0.978	0.985	0.923	0.850	0.927	0.869	0.933	0.872	0.102	0.530	0.000	0.469	0.666	0.502	0.297	**0.000**	**0.000**
Logistic STAR - SRF	0.888	0.989	0.989	0.989	0.995	0.989	0.958	0.985	0.952	0.996	0.968	0.100	0.287	0.470	0.000	0.711	0.528	0.052	**0.000**	**0.000**
TAR - Tbill	0.830	0.964	0.957	0.961	0.964	0.906	0.869	0.906	0.873	0.913	0.878	0.116	0.797	0.815	0.797	0.000	0.370	0.164	**0.000**	**0.000**
TAR - SRF	0.226	0.996	0.994	0.995	0.991	0.657	0.469	0.643	0.515	0.599	0.503	0.089	0.177	0.219	0.177	0.170	0.000	0.338	**0.000**	**0.000**
Logistic STAR - GARCH	0.270	0.983	0.982	0.982	0.991	0.954	0.853	0.954	0.870	0.976	0.885	0.096	**0.046**	0.243	**0.046**	0.131	0.729	0.000	**0.000**	**0.000**
MS Two-state Homoskedastic	**0.009**	**0.027**	**0.017**	**0.016**	**0.028**	**0.009**	**0.006**	**0.009**	**0.005**	**0.012**	**0.006**	**0.046**	**0.008**	**0.015**	**0.008**	**0.029**	**0.004**	**0.013**	0.000	0.705
MS Two-state Heteroskedastic	**0.011**	**0.045**	**0.022**	**0.024**	**0.034**	**0.010**	**0.007**	**0.011**	**0.006**	**0.014**	**0.007**	**0.048**	**0.010**	**0.017**	**0.010**	**0.031**	**0.005**	**0.014**	0.927	0.000

Panel D: 12-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.451	0.443	0.127	0.163	0.997	0.938	0.836	0.631	0.999	1.000	0.996	0.904	0.781	0.904	0.900	0.759	0.827	**0.000**	**0.000**
Random walk (with drift)	0.026		0.343	0.076	0.156	0.801	0.756	0.757	0.629	0.818	0.839	0.996	0.814	0.742	0.814	0.840	0.736	0.761	**0.000**	**0.000**
AR(1)	0.029	0.079		0.097	0.178	0.798	0.753	0.756	0.633	0.815	0.836	0.996	0.818	0.743	0.818	0.841	0.739	0.765	**0.000**	**0.000**
Random walk (with drift and GARCH(1,1))	0.070	0.963	0.968		0.865	0.966	0.959	0.973	0.910	0.980	0.980	0.998	0.942	0.917	0.942	0.915	0.864	0.928	**0.000**	**0.000**
AR(1) with GARCH(1,1)	0.079	0.958	0.973	0.234		0.952	0.938	0.964	0.883	0.969	0.969	0.996	0.943	0.910	0.943	0.918	0.859	0.931	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors	0.928	0.963	0.961	0.934	0.927		0.167	0.316	0.195	0.430	0.667	0.992	0.675	0.483	0.675	0.795	0.545	0.528	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors - t dist.	0.910	0.961	0.959	0.929	0.922	0.016		0.439	0.256	0.702	0.796	0.992	0.737	0.569	0.737	0.820	0.594	0.613	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors	0.919	0.957	0.956	0.932	0.925	0.892	0.928		0.061	0.692	0.738	0.978	0.822	0.615	0.822	0.844	0.630	0.706	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.875	0.948	0.946	0.913	0.907	0.669	0.749	0.004		0.813	0.828	0.978	0.904	0.756	0.904	0.889	0.713	0.861	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors	0.975	0.975	0.973	0.951	0.943	0.272	0.383	0.154	0.296		0.852	0.988	0.705	0.501	0.705	0.796	0.556	0.551	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.936	0.981	0.979	0.958	0.949	0.162	0.192	0.127	0.204	0.098		0.989	0.628	0.446	0.628	0.757	0.518	0.484	**0.000**	**0.000**
Exponential STAR - TBILL	0.952	0.966	0.967	0.962	0.963	0.945	0.946	0.940	0.942	0.946	0.949		0.067	**0.033**	0.067	0.121	0.051	0.055	**0.000**	**0.000**
Exponential STAR - SRF	0.994	0.996	0.996	0.986	0.985	0.949	0.953	0.848	0.911	0.962	0.975	0.065		0.260	0.857	0.810	0.269	0.130	**0.000**	**0.000**
Logistic STAR - TBILL	0.961	0.976	0.975	0.954	0.948	0.921	0.931	0.781	0.887	0.900	0.913	0.057	0.235		0.740	0.885	0.570	0.587	**0.000**	**0.000**
Logistic STAR - SRF	0.994	0.996	0.996	0.986	0.985	0.949	0.953	0.848	0.911	0.962	0.975	0.065	0.953	0.765		0.810	0.269	0.130	**0.000**	**0.000**
TAR - Tbill	0.962	0.972	0.971	0.956	0.955	0.952	0.954	0.937	0.956	0.946	0.945	0.084	0.823	0.921	0.823		0.177	0.129	**0.000**	**0.001**
TAR - SRF	0.965	0.998	0.997	0.988	0.988	0.644	0.676	0.495	0.587	0.730	0.886	0.055	0.050	0.332	0.050	0.111		0.409	**0.000**	**0.000**
Logistic STAR - GARCH	0.997	0.996	0.996	0.986	0.984	0.904	0.917	0.717	0.823	0.943	0.971	0.060	**0.032**	0.482	**0.032**	0.117	0.841		**0.000**	**0.000**
MS Two-state Homoskedastic	**0.002**	**0.017**	**0.045**	**0.012**	**0.019**	**0.006**	**0.007**	**0.010**	**0.012**	**0.003**	**0.002**	**0.030**	**0.000**	**0.004**	**0.000**	**0.010**	**0.000**	**0.000**		0.543
MS Two-state Heteroskedastic	**0.002**	**0.003**	**0.016**	**0.005**	**0.009**	**0.006**	**0.007**	**0.011**	**0.013**	**0.003**	**0.002**	**0.030**	**0.000**	**0.004**	**0.000**	**0.011**	**0.000**	**0.000**	1.000	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) test of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values under a symmetric, square loss function; below the main diagonal, in each cell we show DM p-values obtained under an asymmetric linex loss function.

Table 5

Giacomini-White Equal Conditional Predictive Accuracy Tests, Stock Returns

Panel A: 1-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.941	0.940	0.921	0.985	0.130	0.387	0.835	0.910	0.692	0.746	0.493	0.939	0.085	0.207	0.236	0.085	0.178	**0.000**	**0.047**
Random walk (with drift)	**0.005**		0.071	0.194	0.389	0.445	0.228	0.071	0.301	0.107	0.509	0.882	0.665	0.328	1.000	0.097	0.168	0.730	**0.001**	0.076
AR(1)	**0.006**	0.527		0.067	0.636	0.454	0.207	0.100	0.328	0.133	0.488	0.848	0.699	0.309	0.996	0.097	0.174	0.739	**0.001**	0.068
Random walk (with drift and GARCH(1,1))	**0.006**	**0.049**	0.629		0.608	0.439	0.207	0.058	0.281	0.086	0.494	0.891	0.624	0.321	0.998	0.069	0.155	0.731	**0.001**	0.080
AR(1) with GARCH(1,1)	**0.005**	0.349	**0.000**	0.902		0.408	0.207	0.075	0.302	0.137	0.517	0.822	0.592	0.315	0.980	0.122	0.139	0.865	**0.001**	0.074
GARCH (1,1) in mean and exogenous predictors	0.182	**0.001**	**0.002**	**0.003**	**0.000**		0.142	0.542	0.306	0.562	0.144	0.062	0.280	0.090	0.130	0.243	0.321	0.453	**0.000**	**0.021**
GARCH (1,1) in mean and exogenous predictors - t dist.	1.000	0.372	0.378	0.387	0.346	1.000		**0.042**	0.423	0.002	0.739	0.439	0.393	0.153	0.316	**0.004**	**0.028**	0.066	**0.003**	0.286
EGARCH (1,1) in mean and exogenous predictors	0.054	**0.018**	**0.031**	0.123	1.000	0.098	0.034		**0.027**	0.732	0.070	0.647	0.957	0.203	0.870	0.883	0.443	0.988	**0.000**	0.091
EGARCH (1,1) in mean and exogenous predictors- t dist.	**0.000**	1.000	0.226	**0.028**	0.913	1.000	0.469	**0.008**		0.098	0.214	0.871	0.762	0.233	0.815	0.326	0.120	0.490	**0.001**	0.173
TGARCH (1,1) in mean and exogenous predictors	**0.023**	**0.000**	**0.043**	**0.005**	**0.001**	**0.000**	0.055	0.862	**0.004**		**0.012**	0.556	0.820	0.185	0.749	0.392	0.399	0.930	**0.001**	0.067
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.096	**0.028**	0.022	**0.040**	0.051	0.506	0.082	0.291	0.053	0.146		0.926	0.746	0.132	0.647	0.113	0.068	0.224	**0.001**	0.188
Exponential STAR - TBILL	0.813	**0.006**	**0.015**	**0.006**	**0.006**	0.439	0.001	0.086	**0.000**	**0.002**	0.482		0.741	0.265	0.394	0.297	0.064	0.153	**0.000**	0.104
Exponential STAR - SRF	0.813	**0.007**	**0.009**	**0.008**	**0.009**	0.778	0.005	0.381	**0.045**	0.076	0.164	0.900		0.198	0.982	0.798	0.095	0.387	**0.000**	0.085
Logistic STAR - TBILL	0.073	0.355	0.373	0.375	0.444	0.100	0.561	0.328	0.496	0.497	0.330	0.084	0.110		0.081	0.164	0.073	0.163	0.117	0.517
Logistic STAR - SRF	**0.003**	**0.004**	**0.005**	**0.005**	**0.004**	0.526	0.015	0.110	**0.000**	0.053	0.081	0.249	0.786	**0.046**		0.347	0.103	0.414	**0.000**	**0.047**
TAR - Tbill	**0.001**	**0.009**	**0.010**	**0.012**	**0.008**	**0.018**	0.012	0.269	**0.000**	**0.031**	1.000	**0.009**	**0.044**	0.085	**0.004**		0.124	0.961	**0.000**	**0.027**
TAR - SRF	0.319	**0.000**	**0.001**	**0.001**	**0.000**	0.305	0.001	0.092	**0.000**	**0.005**	**0.004**	0.482	0.994	**0.047**	0.393	0.235		0.478	**0.000**	**0.019**
Logistic STAR - GARCH	**0.000**	**0.006**	**0.007**	**0.009**	**0.007**	0.605	0.000	0.119	**0.000**	0.085	**0.009**	0.179	0.641	0.075	0.114	0.257	0.122		**0.000**	**0.012**
MS Two-state Homoskedastic	**0.001**	**0.018**	**0.018**	**0.016**	**0.013**	**0.000**	**0.048**	**0.005**	**0.026**	**0.034**	**0.026**	**0.004**	0.056	0.366	**0.001**	**0.000**	**0.000**	**0.006**		0.530
MS Two-state Heteroskedastic	**0.018**	0.094	0.079	0.088	0.052	0.255	0.148	**0.007**	**0.048**	**0.031**	0.080	**0.000**	0.398	0.485	**0.015**	**0.060**	**0.009**	**0.004**	0.384	

Panel B: 12-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.155	0.147	0.151	0.161	0.380	0.497	0.359	0.333	**0.034**	0.844	0.637	0.580	0.331	0.203	0.738	0.234	0.587	0.146	0.154
Random walk (with drift)	**0.000**		0.403	0.570	0.327	0.111	0.084	0.277	0.271	0.087	0.142	0.902	0.742	0.161	0.286	0.534	0.329	0.511	**0.046**	0.154
AR(1)	0.056	0.938		0.455	0.230	0.154	0.165	0.298	0.292	0.149	0.243	0.935	0.847	0.467	0.389	0.428	0.279	0.594	0.150	0.175
Random walk (with drift and GARCH(1,1))	0.959	1.000	0.910		0.416	0.096	0.071	0.274	0.268	0.083	0.122	0.877	0.722	0.033	0.280	0.568	0.315	0.506	0.054	0.152
AR(1) with GARCH(1,1)	0.439	1.000	1.000	0.975		0.161	0.133	0.291	0.281	0.124	0.180	0.964	0.826	0.227	0.348	0.388	0.298	0.537	0.109	0.167
GARCH (1,1) in mean and exogenous predictors	0.726	0.951	0.840	0.860	0.087		0.784	0.356	0.351	**0.023**	0.757	0.456	0.363	0.317	0.202	0.841	0.211	0.575	0.114	0.129
GARCH (1,1) in mean and exogenous predictors - t dist.	**0.000**	0.054	**0.000**	1.000	0.513	0.488		0.335	0.320	0.065	0.813	0.567	0.502	0.265	0.240	0.883	0.271	0.567	0.126	0.141
EGARCH (1,1) in mean and exogenous predictors	0.823	0.652	0.651	0.663	0.571	0.838	0.777		0.455	0.442	0.354	0.303	0.411	0.185	0.367	0.336	0.447	0.365	0.202	0.181
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.871	0.616	0.611	0.625	0.652	0.852	0.818	0.999		0.387	0.370	0.307	0.385	0.255	0.391	0.403	0.371	0.175	0.145	0.143
TGARCH (1,1) in mean and exogenous predictors	0.498	1.000	0.694	0.922	0.691	0.075	0.559	0.922	0.883		0.249	0.481	0.337	0.273	0.166	0.634	0.229	0.629	0.109	0.119
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.984	0.480	**0.001**	0.528	0.524	**0.001**	0.760	0.775	0.861	**0.021**		0.434	0.386	0.201	0.201	0.916	0.229	0.541	0.118	0.134
Exponential STAR - TBILL	0.849	1.000	0.782	1.000	0.731	0.930	0.922	**0.000**	**0.000**	0.718	0.886		0.066	0.619	0.271	0.619	0.252	0.108	0.123	0.117
Exponential STAR - SRF	0.367	0.875	0.873	0.903	0.831	0.737	0.803	0.917	0.982	0.684	0.636	0.819		0.236	0.197	0.733	0.198	0.422	0.123	0.112
Logistic STAR - TBILL	0.833	0.808	0.827	0.807	0.820	0.854	0.804	0.436	0.945	0.858	0.833	0.563	0.935		0.302	0.359	0.075	0.249	0.129	0.150
Logistic STAR - SRF	0.865	0.822	0.804	0.828	0.812	0.869	0.905	0.508	0.969	0.996	0.874	0.935	0.893	0.451		0.370	0.066	1.000	0.139	0.124
TAR - Tbill	0.783	0.870	0.684	0.895	0.913	0.846	0.803	0.198	1.000	0.893	0.803	0.652	0.898	0.874	0.619		0.111	0.407	0.137	0.125
TAR - SRF	1.000	0.603	0.661	0.582	0.616	0.809	1.000	0.888	0.720	0.790	0.935	1.000	0.993	**0.000**	0.779	0.774		0.427	0.065	0.081
Logistic STAR - GARCH	1.000	0.652	0.939	0.631	0.453	0.503	0.544	1.000	0.821	0.079	0.427	0.593	0.853	0.790	0.094	0.597	0.862		0.105	0.068
MS Two-state Homoskedastic	0.580	**0.007**	0.664	0.963	0.860	0.661	0.538	0.755	0.913	0.870	0.524	0.542	**0.000**	**0.022**	0.713	0.719	0.828	0.725		0.435
MS Two-state Heteroskedastic	0.742	0.797	0.784	0.797	0.760	0.722	0.737	0.697	0.649	0.689	0.744	1.000	0.616	0.620	0.827	0.706	0.866	0.663	0.653	

Note: The table presents p-values for Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report GW p-values with q=2; below the main diagonal, in each cell we show GW p-values with q=7.

Table 5 [continued]

Giacomini-White Equal Conditional Predictive Accuracy Tests, Bond Returns

Panel C: 1-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.768	0.317	0.764	0.474	0.815	0.341	0.383	0.621	0.800	0.387	0.194	0.674	0.780	0.674	0.448	0.678	0.942	**0.000**	**0.000**
Random walk (with drift)	**0.008**		0.444	1.000	0.634	0.794	0.802	0.670	0.778	0.822	0.871	0.124	0.646	0.685	0.646	0.463	0.603	0.676	**0.000**	**0.001**
AR(1)	**0.016**	0.122		0.231	**0.040**	0.563	0.452	0.700	0.735	0.684	0.655	0.154	0.351	0.555	0.351	0.092	0.645	0.418	**0.000**	**0.000**
Random walk (with drift and GARCH(1,1))	**0.013**	0.064	0.158		0.304	0.776	0.772	0.607	0.736	0.814	0.859	0.118	0.634	0.689	0.634	0.429	0.594	0.656	**0.000**	**0.000**
AR(1) with GARCH(1,1)	**0.018**	**0.000**	0.081	0.295		0.693	0.584	0.745	0.826	0.789	0.794	0.132	0.438	0.584	0.438	0.104	0.663	0.504	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors	0.098	**0.015**	**0.021**	**0.025**	0.073		0.755	0.442	0.822	0.504	0.552	0.173	0.288	0.474	0.288	0.183	0.840	0.243	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors - t dist.	0.153	**0.005**	**0.006**	**0.008**	**0.013**	**0.010**		0.121	0.992	0.310	0.922	0.141	0.203	0.364	0.203	0.277	0.750	0.416	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors	0.157	**0.010**	**0.033**	**0.021**	0.128	0.780	0.297		0.419	0.326	0.440	0.147	0.112	0.579	0.112	0.240	0.646	0.154	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.867	**0.003**	**0.002**	**0.006**	**0.008**	0.177	0.732	0.366		0.856	0.853	0.166	0.266	0.459	0.266	0.320	0.774	0.581	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors	0.120	**0.017**	**0.030**	**0.028**	0.092	0.095	1.000	0.499	**0.000**		0.464	0.169	0.182	0.673	0.182	0.186	0.845	0.145	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors- t dist.	1.000	**0.005**	**0.003**	**0.008**	**0.005**	**0.008**	0.737	0.077	0.843	0.182		0.133	0.088	0.550	0.088	0.228	0.660	0.203	**0.000**	**0.000**
Exponential STAR - TBILL	0.540	**0.000**	**0.012**	1.000	**0.021**	0.524	0.549	0.182	0.505	0.987	0.530		0.266	0.366	0.266	0.396	0.405	0.232	**0.001**	**0.003**
Exponential STAR - SRF	0.385	**0.011**	**0.038**	**0.018**	0.069	0.050	0.149	0.483	0.846	1.000	0.640	0.347		0.785	NaN	0.583	0.706	0.341	**0.000**	**0.000**
Logistic STAR - TBILL	0.211	**0.045**	0.138	0.071	0.226	0.368	0.534	0.456	0.458	0.290	0.608	**0.027**	0.268		0.785	0.515	0.873	0.701	**0.001**	**0.001**
Logistic STAR - SRF	0.385	**0.011**	**0.038**	**0.018**	0.069	0.050	0.149	0.483	0.846	1.000	0.640	0.347	NaN	0.268		0.583	0.706	0.341	**0.000**	**0.000**
TAR - Tbill	0.072	0.067	**0.048**	0.093	**0.046**	0.125	0.110	0.188	0.267	0.154	0.104	0.252	0.137	0.454	0.137		0.590	0.370	**0.000**	**0.001**
TAR - SRF	0.488	**0.010**	**0.047**	**0.024**	0.075	0.439	0.361	0.551	0.508	0.674	0.193	0.057	0.448	0.877	0.448	0.386		0.890	**0.001**	**0.001**
Logistic STAR - GARCH	0.862	**0.011**	**0.032**	**0.019**	0.081	**0.017**	0.113	0.968	0.819	**0.007**	0.148	0.489	0.108	0.554	0.108	0.139	0.422		**0.000**	**0.000**
MS Two-state Homoskedastic	**0.000**	**0.010**	**0.000**	**0.005**	**0.000**	**0.000**	**0.001**	**0.006**	**0.005**	**0.003**	**0.001**	**0.009**	**0.001**	0.770	**0.001**	**0.001**	**0.018**	**0.001**		0.644
MS Two-state Heteroskedastic	**0.000**	**0.015**	**0.005**	**0.012**	**0.005**	**0.003**	**0.000**	**0.004**	**0.005**	**0.009**	**0.002**	**0.008**	**0.002**	0.829	**0.002**	**0.000**	**0.015**	**0.000**	0.110	

Panel D: 12-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.700	0.765	0.188	0.261	0.213	0.422	0.484	0.364	**0.005**	0.081	**0.000**	0.300	0.682	0.300	0.338	0.486	0.421	0.129	0.104
Random walk (with drift)	1.000		1.000	**0.000**	**0.015**	1.000	0.564	0.797	0.273	0.570	0.610	**0.024**	0.393	0.708	0.393	0.637	0.691	0.444	0.091	0.076
AR(1)	0.204	0.481		**0.000**	1.000	1.000	0.501	0.685	**0.013**	0.467	0.528	**0.008**	0.434	0.709	0.434	0.637	0.681	0.495	0.099	0.094
Random walk (with drift and GARCH(1,1))	0.058	0.342	0.927		0.591	0.325	0.391	0.199	0.525	0.288	0.282	0.074	0.141	0.334	0.141	0.485	0.321	0.186	0.144	0.072
AR(1) with GARCH(1,1)	0.860	0.385	0.778	0.940		0.405	0.447	0.342	0.575	0.353	0.335	0.065	0.143	0.346	0.143	0.486	0.355	0.172	0.135	**0.043**
GARCH (1,1) in mean and exogenous predictors	0.869	0.999	0.913	0.736	0.836		0.398	0.756	0.518	0.844	0.352	**0.000**	0.571	0.891	0.571	0.585	0.712	0.662	0.133	0.103
GARCH (1,1) in mean and exogenous predictors - t dist.	0.939	1.000	0.973	0.772	0.851	**0.009**		0.932	0.748	0.803	0.424	**0.000**	0.711	0.935	0.711	0.697	0.811	0.821	0.136	0.140
EGARCH (1,1) in mean and exogenous predictors	0.992	0.193	0.219	**0.000**	0.807	0.840	0.489		0.405	0.821	0.759	**0.000**	1.000	0.564	1.000	0.453	0.244	**0.000**	0.138	0.097
EGARCH (1,1) in mean and exogenous predictors- t dist.	1.000	**0.000**	0.805	1.000	0.878	0.369	0.667	0.475		0.654	0.597	**0.000**	**0.000**	0.469	**0.000**	0.500	0.266	**0.023**	0.147	0.133
TGARCH (1,1) in mean and exogenous predictors	0.734	0.630	0.947	0.810	0.890	1.000	1.000	0.347	0.682		0.215	**0.000**	0.410	0.886	0.410	0.723	0.629	0.626	0.130	0.134
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.603	**0.000**	0.076	0.844	0.707	0.631	1.000	0.508	**0.000**	0.810		**0.000**	0.779	0.903	0.779	0.797	0.754	0.770	0.121	0.143
Exponential STAR - TBILL	**0.000**	0.142	0.416	1.000	1.000	**0.000**	0.075	**0.000**	1.000	**0.000**	**0.001**		1.000	1.000	1.000	**0.020**	1.000	1.000	**0.000**	**0.000**
Exponential STAR - SRF	1.000	0.527	0.560	0.814	0.520	1.000	0.972	**0.004**	0.320	**0.000**	0.302	0.941		0.957	0.368	0.615	0.831	**0.010**	0.112	0.129
Logistic STAR - TBILL	0.551	0.323	0.368	0.611	0.576	0.764	0.679	**0.002**	0.459	0.598	0.658	0.574	0.907		0.957	0.247	0.367	0.493	0.141	0.158
Logistic STAR - SRF	1.000	0.527	0.560	0.814	0.520	1.000	0.972	**0.004**	0.320	**0.000**	0.302	0.941	0.426	0.907		0.615	0.831	**0.010**	0.112	0.129
TAR - Tbill	**0.000**	1.000	1.000	0.510	1.000	0.943	0.930	0.865	0.966	0.912	0.886	0.909	0.452	0.690	0.452		0.547	0.466	0.146	0.164
TAR - SRF	0.819	0.458	0.657	0.764	0.781	0.762	0.866	0.946	1.000	0.820	0.808	1.000	0.798	0.892	0.798	0.913		0.523	0.118	0.133
Logistic STAR - GARCH	1.000	0.547	0.682	0.774	0.239	**0.023**	1.000	1.000	0.091	**0.040**	0.464	0.934	0.984	1.000	0.984	0.373	0.949		0.105	0.139
MS Two-state Homoskedastic	0.649	0.654	0.808	1.000	0.227	0.563	0.489	0.419	**0.000**	0.422	0.609	**0.000**	1.000	0.570	1.000	**0.044**	0.912	0.860		1.000
MS Two-state Heteroskedastic	0.533	0.335	1.000	0.607	0.324	0.495	1.000	0.207	**0.000**	0.842	0.338	**0.000**	0.556	0.538	0.556	**0.009**	0.060	0.497	**0.000**	

Note: The table presents p-values for Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report GW p-values with q=2; below the main diagonal, in each cell we show GW p-values with q=7.

Table 6

Van Dijk-Franses Equal Predictive Accuracy Tests: Stock Return Forecasts, Asymmetric Weighting Functions

Panel A: 1-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.999	1.000	0.999	0.999	0.946	0.992	0.974	0.994	0.989	0.958	0.089	0.548	0.573	0.212	0.977	0.800	0.959	**0.000**	**0.016**
Random walk (with drift)	**0.000**		0.318	0.009	0.378	**0.012**	**0.005**	**0.010**	**0.041**	0.060	**0.001**	**0.002**	**0.003**	0.056	**0.001**	**0.001**	**0.026**	**0.001**	**0.000**	**0.001**
AR(1)	**0.000**	0.982		0.159	0.499	**0.011**	**0.007**	**0.012**	0.052	0.075	**0.001**	**0.002**	**0.003**	0.056	**0.001**	**0.001**	**0.024**	**0.001**	**0.000**	**0.001**
Random walk (with drift and GARCH(1,1))	**0.000**	0.986	0.329		0.769	**0.014**	**0.009**	**0.018**	0.076	0.084	**0.001**	**0.003**	**0.003**	0.066	**0.001**	**0.001**	**0.032**	**0.002**	**0.000**	**0.001**
AR(1) with GARCH(1,1)	**0.000**	0.992	0.536	0.728		**0.014**	**0.006**	**0.013**	0.057	0.059	**0.001**	**0.004**	**0.003**	0.066	**0.002**	**0.001**	**0.032**	**0.003**	**0.000**	**0.001**
GARCH (1,1) in mean and exogenous predictors	0.966	0.999	0.999	0.999	0.999		0.907	0.833	0.939	0.934	0.737	**0.030**	0.204	0.423	**0.028**	0.633	0.439	0.441	**0.000**	**0.013**
GARCH (1,1) in mean and exogenous predictors - t dist.	**0.000**	0.638	0.550	0.573	0.547	**0.000**		0.414	0.860	0.785	0.125	**0.016**	0.053	0.221	**0.012**	**0.040**	0.153	**0.044**	**0.001**	**0.007**
EGARCH (1,1) in mean and exogenous predictors	0.071	0.998	0.997	0.998	0.997	**0.025**	1.000		0.906	0.811	0.170	**0.026**	0.066	0.218	**0.033**	0.168	0.189	0.079	**0.001**	**0.006**
EGARCH (1,1) in mean and exogenous predictors- t dist.	**0.000**	0.771	0.687	0.711	0.688	**0.001**	0.845	**0.000**		0.445	**0.002**	**0.009**	**0.025**	0.125	**0.009**	**0.043**	0.094	**0.013**	**0.001**	**0.004**
TGARCH (1,1) in mean and exogenous predictors	**0.017**	0.991	0.986	0.988	0.987	**0.006**	0.999	0.241	1.000		**0.033**	**0.020**	**0.023**	0.192	**0.012**	**0.034**	0.127	**0.048**	**0.001**	**0.006**
TGARCH (1,1) in mean and exogenous predictors- t dist.	**0.000**	0.967	0.948	0.956	0.952	**0.002**	1.000	**0.006**	0.999	**0.022**		**0.043**	0.094	0.296	0.052	0.306	0.286	0.152	**0.002**	**0.010**
Exponential STAR - TBILL	0.608	1.000	1.000	1.000	1.000	**0.028**	1.000	0.919	1.000	0.982	1.000		0.772	0.739	0.876	0.960	0.990	0.978	**0.000**	**0.046**
Exponential STAR - SRF	0.589	1.000	0.999	1.000	1.000	0.064	1.000	0.912	1.000	0.948	0.997	0.545		0.550	0.382	0.861	0.670	0.732	**0.003**	**0.031**
Logistic STAR - TBILL	**0.001**	0.925	0.890	0.902	0.893	**0.005**	0.934	**0.044**	0.859	0.102	0.300	**0.003**	**0.002**		0.403	0.611	0.559	0.574	**0.032**	0.063
Logistic STAR - SRF	0.945	1.000	1.000	1.000	1.000	**0.039**	1.000	0.947	1.000	0.988	1.000	0.689	0.516	0.999		0.984	0.851	0.938	**0.000**	**0.018**
TAR - Tbill	0.577	1.000	1.000	1.000	1.000	**0.047**	1.000	0.928	1.000	0.979	1.000	0.494	0.455	0.999	0.363		0.370	0.318	**0.001**	**0.011**
TAR - SRF	0.975	1.000	1.000	1.000	1.000	0.132	1.000	0.987	1.000	0.999	1.000	0.971	0.855	1.000	0.944	0.931		0.518	**0.000**	**0.003**
Logistic STAR - GARCH	0.830	1.000	1.000	1.000	1.000	0.057	1.000	0.956	1.000	0.993	1.000	0.749	0.537	1.000	0.569	0.697	0.079		**0.000**	**0.005**
MS Two-state Homoskedastic	**0.003**	0.681	0.624	0.633	0.615	**0.005**	0.571	0.025	0.481	0.066	0.168	**0.005**	**0.004**	0.241	**0.002**	**0.001**	**0.001**	**0.002**		0.815
MS Two-state Heteroskedastic	0.069	0.897	0.885	0.881	0.873	**0.020**	0.814	0.265	0.777	0.325	0.511	0.065	0.098	0.609	0.058	**0.042**	**0.025**	**0.043**	0.834	

Panel B: 12-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.956	0.976	0.936	0.941	0.276	0.967	0.605	0.723	0.938	0.878	**0.006**	**0.011**	**0.019**	**0.009**	**0.010**	0.060	0.070	**0.013**	**0.015**
Random walk (with drift)	**0.000**		0.928	**0.024**	0.767	**0.037**	0.468	0.401	0.579	0.194	0.224	**0.007**	**0.009**	**0.023**	**0.013**	**0.011**	**0.043**	**0.043**	**0.009**	**0.011**
AR(1)	**0.000**	**0.000**		0.063	0.054	**0.021**	0.096	0.303	0.486	0.059	0.080	**0.010**	**0.019**	**0.021**	**0.014**	**0.010**	**0.043**	**0.048**	**0.012**	**0.014**
Random walk (with drift and GARCH(1,1))	**0.000**	0.999	1.000		0.836	0.053	0.563	0.422	0.596	0.264	0.287	**0.008**	**0.009**	**0.025**	**0.014**	**0.014**	**0.046**	**0.045**	**0.009**	**0.011**
AR(1) with GARCH(1,1)	**0.000**	1.000	1.000	**0.000**		**0.044**	0.341	0.380	0.551	0.155	0.169	**0.011**	**0.018**	**0.024**	**0.016**	**0.014**	**0.048**	0.050	**0.011**	**0.013**
GARCH (1,1) in mean and exogenous predictors	0.824	1.000	1.000	1.000	1.000		0.990	0.627	0.738	1.000	0.979	**0.004**	**0.004**	**0.012**	**0.007**	**0.003**	0.056	0.074	**0.011**	**0.012**
GARCH (1,1) in mean and exogenous predictors - t dist.	**0.001**	1.000	1.000	1.000	1.000	**0.000**		0.412	0.584	**0.043**	0.134	**0.006**	**0.011**	**0.013**	**0.009**	**0.002**	**0.040**	0.053	**0.010**	**0.011**
EGARCH (1,1) in mean and exogenous predictors	0.971	0.997	0.997	0.996	0.997	0.969	0.987		0.774	0.505	0.515	**0.000**	**0.000**	**0.004**	**0.000**	**0.030**	**0.022**	**0.001**	**0.003**	**0.003**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.992	1.000	1.000	1.000	1.000	0.993	0.998	0.479		0.353	0.357	**0.000**	**0.002**	**0.000**	**0.000**	**0.031**	**0.003**	**0.000**	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors	1.000	1.000	1.000	1.000	1.000	0.999	1.000	0.046	0.012		0.601	**0.006**	**0.014**	**0.013**	**0.008**	**0.003**	**0.043**	0.062	**0.010**	**0.011**
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.295	1.000	1.000	1.000	1.000	0.064	1.000	0.020	0.005	0.000		**0.004**	**0.008**	**0.010**	**0.006**	**0.004**	**0.041**	**0.049**	**0.007**	**0.008**
Exponential STAR - TBILL	0.946	0.993	0.994	0.991	0.993	0.918	0.972	0.136	0.119	0.849	0.944		1.000	0.534	0.936	0.910	1.000	0.689	0.088	0.069
Exponential STAR - SRF	0.978	0.998	0.998	0.997	0.998	0.953	0.990	0.116	0.061	0.877	0.967	0.331		0.089	**0.003**	0.374	0.110	0.071	**0.013**	**0.011**
Logistic STAR - TBILL	0.757	0.990	0.994	0.986	0.992	0.689	0.896	0.044	0.033	0.514	0.780	**0.030**	0.054		0.698	0.873	0.844	0.586	0.132	0.180
Logistic STAR - SRF	0.966	0.992	0.993	0.991	0.992	0.951	0.979	0.216	0.223	0.916	0.968	0.983	0.855	0.983		0.876	0.919	0.503	0.061	0.063
TAR - Tbill	0.952	0.996	0.998	0.995	0.997	0.922	0.980	0.095	0.085	0.830	0.951	0.253	0.484	0.985	**0.047**		0.302	0.297	0.070	0.064
TAR - SRF	0.995	1.000	1.000	1.000	1.000	0.987	0.998	0.159	0.105	0.960	0.992	0.753	1.000	0.996	0.319	0.863		0.261	**0.011**	**0.002**
Logistic STAR - GARCH	0.997	0.999	0.999	0.999	0.999	0.995	0.998	0.624	0.622	0.992	0.997	0.999	0.992	0.999	1.000	0.997	0.985		**0.014**	**0.000**
MS Two-state Homoskedastic	**0.000**	**0.039**	0.053	**0.026**	**0.032**	**0.000**	**0.001**	**0.003**	**0.000**	**0.000**	**0.000**	**0.006**	**0.001**	**0.006**	**0.007**	**0.004**	**0.000**	**0.002**		0.670
MS Two-state Heteroskedastic	**0.000**	**0.006**	**0.008**	**0.002**	**0.005**	**0.000**	**0.001**	**0.001**	**0.000**	**0.000**	**0.000**	**0.004**	**0.002**	**0.002**	**0.004**	**0.002**	**0.000**	**0.000**	0.401	

Note: The table presents p-values for Diebold and Mariano's test of no differential in predictive accuracy when loss function differences are weighted as proposed by van Dijk and Franses (2003). Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report vDF p-values under a symmetric, square loss function where weights is attached only to loss differences below the median; below the main diagonal, we report vDF p-values where weights is attached only to loss differences above the median.

Table 6 [continued]

Van Dijk-Franses Equal Predictive Accuracy Tests: Bond Return Forecasts, Asymmetric Weighting Functions

Panel C: 1-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.997	1.000	0.994	0.999	0.970	0.647	0.882	0.524	0.962	0.470	0.958	0.747	0.779	0.747	0.963	0.885	0.720	**0.000**	**0.000**
Random walk (with drift)	**0.000**		0.100	**0.004**	**0.049**	0.017	**0.003**	**0.012**	**0.004**	**0.018**	**0.003**	0.365	**0.009**	**0.036**	**0.009**	**0.026**	**0.039**	**0.008**	**0.000**	**0.000**
AR(1)	**0.000**	1.000		0.793	0.089	0.022	**0.000**	**0.013**	**0.001**	**0.022**	**0.001**	0.624	**0.006**	**0.040**	**0.006**	0.069	0.090	**0.005**	**0.000**	**0.000**
Random walk (with drift and GARCH(1,1))	**0.000**	0.999	**0.026**		0.113	0.029	**0.005**	**0.022**	**0.007**	**0.030**	**0.006**	0.460	**0.015**	0.056	**0.015**	**0.042**	0.068	**0.015**	**0.000**	**0.000**
AR(1) with GARCH(1,1)	**0.000**	1.000	0.959	0.998		0.034	**0.001**	**0.023**	**0.003**	**0.034**	**0.002**	0.682	**0.011**	0.066	**0.011**	0.096	0.131	**0.009**	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors	**0.001**	1.000	1.000	1.000	0.999		**0.007**	0.155	**0.030**	0.293	**0.004**	0.897	**0.036**	0.359	**0.036**	0.720	0.591	**0.010**	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors - t dist.	**0.030**	1.000	1.000	1.000	1.000	1.000		0.910	0.416	0.983	0.305	0.955	0.636	0.718	0.636	0.944	0.862	0.640	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors	**0.020**	1.000	1.000	1.000	1.000	0.664	0.097		**0.044**	0.801	**0.025**	0.922	0.164	0.507	0.164	0.812	0.718	0.155	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.112	1.000	1.000	1.000	1.000	0.988	0.593	0.987		0.961	0.420	0.955	0.665	0.746	0.665	0.931	0.887	0.671	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors	**0.002**	1.000	0.999	1.000	0.999	0.588	0.003	0.392	**0.022**		0.007	0.902	0.038	0.382	0.038	0.752	0.616	**0.010**	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors- t dist.	**0.041**	1.000	1.000	1.000	1.000	0.999	0.450	0.916	0.377	0.998		0.957	0.751	0.771	0.751	0.956	0.910	0.766	**0.000**	**0.000**
Exponential STAR - TBILL	0.931	0.999	0.997	0.999	0.996	0.974	0.959	0.971	0.958	0.974	0.960		0.064	0.105	0.064	0.156	0.176	0.065	**0.000**	**0.000**
Exponential STAR - SRF	0.864	1.000	1.000	1.000	1.000	1.000	0.996	0.998	0.975	1.000	0.994	0.081		0.721	0.384	0.937	0.847	0.512	**0.001**	**0.000**
Logistic STAR - TBILL	0.500	1.000	0.999	1.000	0.999	0.908	0.763	0.888	0.744	0.897	0.767	0.079	0.381		0.279	0.765	0.678	0.278	**0.002**	**0.001**
Logistic STAR - SRF	0.864	1.000	1.000	1.000	1.000	1.000	0.996	0.998	0.975	1.000	0.994	0.081	0.312	0.619		0.937	0.847	0.512	**0.001**	**0.000**
TAR - Tbill	0.500	1.000	0.997	0.999	0.996	0.861	0.727	0.828	0.700	0.851	0.728	0.084	0.391	0.501	0.391		0.445	0.054	**0.000**	**0.000**
TAR - SRF	0.332	1.000	0.998	1.000	0.995	0.776	0.577	0.741	0.552	0.754	0.580	0.070	0.235	0.353	0.235	0.371		0.163	**0.000**	**0.000**
Logistic STAR - GARCH	0.208	1.000	1.000	1.000	1.000	1.000	0.939	0.995	0.852	1.000	0.937	0.055	**0.011**	0.374	**0.011**	0.394	0.585		**0.001**	**0.000**
MS Two-state Homoskedastic	**0.000**	0.143	**0.006**	**0.038**	**0.003**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**		0.279
MS Two-state Heteroskedastic	**0.000**	0.285	**0.017**	0.093	**0.008**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	0.961	

Panel D: 12-month Horizon

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.975	0.975	0.603	0.685	0.765	0.661	0.314	0.203	0.752	0.927	0.894	0.189	0.243	0.189	0.394	0.307	0.202	**0.000**	**0.001**
Random walk (with drift)	**0.003**		0.847	**0.004**	**0.013**	0.109	0.072	**0.027**	**0.012**	0.077	0.175	**0.004**	**0.007**	**0.019**	**0.007**	**0.036**	**0.029**	**0.008**	**0.000**	**0.000**
AR(1)	**0.003**	**0.001**		**0.005**	**0.011**	0.104	0.069	**0.024**	**0.010**	0.071	0.165	**0.011**	**0.005**	**0.014**	**0.005**	**0.028**	**0.023**	**0.005**	**0.000**	**0.000**
Random walk (with drift and GARCH(1,1))	0.051	0.956	0.968		0.799	0.555	0.493	0.322	0.231	0.550	0.698	0.865	0.111	0.170	0.111	0.322	0.226	0.120	**0.000**	**0.000**
AR(1) with GARCH(1,1)	**0.041**	0.974	0.981	0.430		0.469	0.406	0.261	0.172	0.459	0.607	0.726	0.056	0.103	0.056	0.223	0.155	0.062	**0.000**	**0.001**
GARCH (1,1) in mean and exogenous predictors	0.957	0.995	0.995	0.966	0.967		0.234	0.167	0.136	0.470	1.000	0.730	0.181	0.221	0.181	0.343	0.287	0.192	**0.000**	**0.002**
GARCH (1,1) in mean and exogenous predictors - t dist.	0.900	0.992	0.992	0.955	0.955	0.081		0.202	0.142	0.688	0.987	0.784	0.189	0.234	0.189	0.370	0.306	0.202	**0.000**	**0.002**
EGARCH (1,1) in mean and exogenous predictors	0.917	0.989	0.989	0.957	0.956	0.742	0.878		0.287	0.932	0.972	0.856	0.232	0.293	0.232	0.471	0.376	0.250	**0.001**	**0.004**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.848	0.985	0.985	0.939	0.937	0.424	0.580	**0.008**		0.934	0.971	0.877	0.235	0.307	0.235	0.510	0.399	0.254	**0.001**	**0.004**
TGARCH (1,1) in mean and exogenous predictors	0.984	0.997	0.997	0.973	0.974	0.405	0.654	0.265	0.521		0.997	0.752	0.162	0.205	0.162	0.338	0.282	0.175	**0.001**	**0.002**
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.971	0.997	0.997	0.971	0.974	0.153	0.328	0.160	0.335	**0.042**		0.580	0.131	0.162	0.131	0.265	0.228	0.141	**0.000**	**0.001**
Exponential STAR - TBILL	0.991	1.000	1.000	0.997	0.997	0.980	0.981	0.965	0.970	0.979	0.983		0.099	0.126	0.099	0.217	0.152	0.104	**0.000**	**0.000**
Exponential STAR - SRF	0.996	1.000	1.000	0.996	0.998	0.957	0.957	0.907	0.933	0.965	0.976	0.053		0.834	0.599	0.977	0.803	0.662	**0.019**	**0.039**
Logistic STAR - TBILL	0.992	1.000	1.000	0.994	0.994	0.930	0.942	0.832	0.881	0.918	0.944	**0.010**	0.166		0.166	0.940	0.620	0.185	**0.019**	**0.037**
Logistic STAR - SRF	0.996	1.000	1.000	0.996	0.998	0.957	0.957	0.907	0.933	0.965	0.976	0.053	0.948	0.834		0.977	0.803	0.662	**0.019**	**0.039**
TAR - Tbill	0.977	0.995	0.995	0.977	0.981	0.933	0.935	0.899	0.922	0.934	0.945	0.095	0.541	0.785	0.541		0.316	**0.010**	**0.007**	**0.017**
TAR - SRF	0.996	1.000	1.000	0.994	0.996	0.894	0.900	0.821	0.872	0.922	0.957	**0.031**	**0.049**	0.496	0.049	0.228		0.238	**0.002**	**0.006**
Logistic STAR - GARCH	0.999	1.000	0.998	0.998	0.999	0.952	0.952	0.880	0.918	0.963	0.978	**0.036**	0.052	0.694	0.052	0.301	0.826		**0.021**	**0.040**
MS Two-state Homoskedastic	**0.000**	**0.021**	0.052	**0.019**	**0.015**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**		0.758
MS Two-state Heteroskedastic	**0.000**	**0.000**	**0.000**	**0.001**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	0.093	

Note: The table presents p-values for Diebold and Mariano's test of no differential in predictive accuracy when loss function differences are weighted as proposed by van Dijk and Franses (2003). Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report vDF p-values under a symmetric, square loss function where weights is attached only to loss differences below the median; below the main diagonal, we report vDF p-values where weights is attached only to loss differences above the median.

Table 7

Sub-Sample Predictive Accuracy Measures for Stock and Bond Returns

Panel A: 1-month Horizon

1995:01-1999:01

Model \ Measure	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	MAFE Stocks	MAFE Bonds	MPFE Stocks	MPFE Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for ϕ_0 and ϕ_1=1) Stocks	MZ (p-value for ϕ_0 and ϕ_1=1) Bonds
Linear	3.915	1.022	1.533	0.473	12.974	0.822	2.985	0.791	1.296	1.115	0.521	0.771	0.067	0.003	0.021	0.000
Random walk (with drift)	3.737	**0.814**	**0.087**	**-0.007**	13.954	**0.662**	**2.680**	**0.645**	0.690	0.956	**0.729**	**0.854**	0.097	**0.062**	**0.085**	**0.204**
AR(1)	3.742	0.867	**0.090**	**0.003**	13.992	0.752	2.680	0.684	**0.645**	0.915	0.729	**0.854**	0.013	0.006	**0.621**	0.042
Random walk (with drift and GARCH(1,1))	**3.720**	0.840	0.136	0.157	13.818	0.681	2.660	0.662	0.705	1.017	0.729	**0.854**	0.009	0.018	**0.896**	**0.133**
AR(1) with GARCH(1,1)	3.757	0.891	0.174	0.147	14.081	0.772	2.690	0.702	0.738	**0.907**	0.729	0.854	0.029	0.005	**0.354**	0.012
GARCH (1,1) in mean and exogenous predictors	4.475	0.970	2.256	0.387	14.935	0.791	3.322	0.752	2.658	1.082	0.458	0.771	0.022	0.000	0.000	0.000
GARCH (1,1) in mean and exogenous predictors - t dist.	**3.608**	0.982	0.369	0.422	**12.879**	0.785	2.615	0.756	0.719	1.052	0.729	0.792	0.078	0.000	**0.689**	0.000
EGARCH (1,1) in mean and exogenous predictors	3.772	0.958	-0.302	0.353	14.137	0.792	2.675	0.750	0.678	1.025	0.708	0.792	0.008	0.000	**0.483**	0.000
EGARCH (1,1) in mean and exogenous predictors- t dist.	3.708	0.964	**0.027**	0.354	13.750	0.803	2.660	0.745	0.869	1.010	0.688	0.792	0.016	0.001	**0.871**	0.000
TGARCH (1,1) in mean and exogenous predictors	3.778	0.974	0.188	0.397	14.235	0.791	2.693	0.757	1.020	1.047	0.625	0.771	0.004	0.000	**0.489**	0.000
TGARCH (1,1) in mean and exogenous predictors- t dist.	3.728	0.981	0.229	0.424	13.849	0.782	2.706	0.759	1.201	1.065	0.646	0.813	0.013	0.000	**0.728**	0.000
Recursive AR(1)	3.742	0.867	0.090	**0.003**	13.992	0.752	2.680	0.684	0.645	0.915	0.729	0.854	0.013	0.006	**0.621**	0.042
Recursive AR(1) with GARCH(1,1)	3.757	0.891	0.174	0.147	14.081	0.772	2.690	0.702	0.738	**0.907**	0.729	0.854	0.029	0.005	**0.354**	0.012
Linear with other asset	4.029	1.013	1.148	0.433	14.919	0.839	2.887	0.781	1.325	1.114	0.542	0.792	0.000	0.004	0.027	0.000
Linear with other asset and GARCH (1,1)	5.237	0.974	2.158	0.365	22.775	0.816	3.665	0.754	3.635	1.062	0.479	0.771	0.001	0.000	0.000	0.000
Exponential STAR - Tbill	3.909	0.988	1.553	0.458	**12.872**	0.766	2.987	0.758	1.359	1.168	0.563	0.771	0.076	0.000	0.018	0.000
Exponential STAR - 1-month forecast	3.967	1.030	1.262	0.481	14.140	0.829	3.038	0.807	1.712	1.114	0.625	0.750	0.047	0.000	0.019	0.000
Logistic STAR - Tbill	3.955	1.001	0.253	0.267	15.579	0.931	2.850	0.783	**0.575**	0.918	0.646	0.792	0.001	0.020	**0.063**	0.000
Logistic STAR - 1-month forecast	3.885	1.030	1.657	0.481	12.349	0.829	2.925	0.807	1.247	1.114	0.563	0.750	**0.117**	0.000	0.009	0.000
TAR - Tbill	3.939	0.977	1.519	0.453	13.209	0.749	3.007	0.755	2.111	1.220	0.500	0.729	0.058	0.025	0.020	0.000
TAR - 1-month forecast	4.111	1.080	1.294	0.311	15.226	1.070	3.180	0.877	0.825	**0.743**	0.542	0.750	0.021	0.007	0.007	0.000
Logistic STAR GARCH(1,1) transition	4.035	0.991	1.423	0.425	14.255	0.803	2.990	0.777	0.950	1.101	0.583	0.750	0.001	0.000	0.025	0.000
TAR with other asset	3.926	0.904	1.065	0.361	14.278	0.686	2.802	0.694	2.046	1.115	0.583	0.771	0.025	0.056	**0.051**	0.002
MS Two-state Homoskedastic	**3.098**	**0.763**	0.848	0.256	**8.876**	**0.516**	**2.212**	**0.599**	0.807	1.077	**0.771**	0.854	**0.531**	**0.260**	0.000	0.017
MS Two-state Heteroskedastic	3.753	**0.792**	0.867	0.353	13.331	**0.503**	**2.504**	**0.648**	**0.592**	0.960	**0.771**	0.833	**0.103**	**0.270**	**0.061**	0.002

1999:02-2003:01

Model \ Measure	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	MAFE Stocks	MAFE Bonds	MPFE Stocks	MPFE Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for ϕ_0 and ϕ_1=1) Stocks	MZ (p-value for ϕ_0 and ϕ_1=1) Bonds
Linear	4.956	1.317	-0.241	0.157	24.500	1.710	3.879	0.995	0.913	-0.231	0.500	0.604	0.000	0.010	**0.499**	**0.112**
Random walk (with drift)	5.207	1.337	-1.853	-0.415	23.684	**1.614**	3.952	1.092	1.132	-2.300	0.521	**0.646**	0.024	**0.150**	0.030	0.002
AR(1)	5.222	1.339	-1.818	-0.293	23.963	1.707	3.984	1.059	1.140	-0.836	0.521	0.646	0.002	0.000	0.043	**0.065**
Random walk (with drift and GARCH(1,1))	5.203	1.327	-1.815	-0.379	23.781	1.619	3.947	1.078	1.114	-2.235	0.521	0.646	0.003	0.024	0.049	**0.056**
AR(1) with GARCH(1,1)	5.213	1.334	-1.852	-0.267	23.745	1.707	3.951	1.034	1.126	-0.941	0.521	0.646	0.004	0.000	0.044	**0.079**
GARCH (1,1) in mean and exogenous predictors	5.190	1.338	**-0.083**	0.080	26.927	1.783	4.039	0.995	0.961	-0.564	0.458	0.625	0.004	0.003	**0.054**	**0.064**
GARCH (1,1) in mean and exogenous predictors - t dist.	5.085	1.324	-1.121	0.126	24.604	1.738	3.875	0.993	1.023	-0.645	0.500	0.625	0.000	0.005	**0.151**	**0.097**
EGARCH (1,1) in mean and exogenous predictors	5.222	1.336	-0.166	0.150	27.242	1.763	4.212	0.990	1.027	-0.273	0.354	0.583	0.086	0.007	0.006	**0.062**
EGARCH (1,1) in mean and exogenous predictors- t dist.	5.114	1.333	-0.908	0.136	25.329	1.758	3.998	1.010	1.024	-0.359	0.438	0.604	0.011	0.002	**0.091**	**0.076**
TGARCH (1,1) in mean and exogenous predictors	5.375	1.339	-0.442	0.084	28.697	1.785	4.296	0.996	1.344	-0.507	0.313	0.646	0.052	0.005	0.004	**0.059**
TGARCH (1,1) in mean and exogenous predictors- t dist.	5.049	1.331	-0.347	0.153	25.375	1.748	4.012	0.995	1.068	-0.421	0.375	0.583	0.008	0.006	**0.176**	**0.076**
Recursive AR(1)	5.222	1.339	-1.818	-0.293	23.963	1.707	3.984	1.059	1.140	-0.836	0.521	0.646	0.002	0.000	0.043	**0.065**
Recursive AR(1) with GARCH(1,1)	5.213	1.334	-1.852	-0.267	23.745	1.707	3.951	1.034	1.126	-0.941	0.521	0.646	0.004	0.000	0.044	**0.079**
Linear with other asset	5.157	**1.313**	-0.398	0.090	26.435	1.717	4.020	0.986	0.825	-0.747	0.458	0.563	0.007	0.016	**0.068**	**0.108**
Linear with other asset and GARCH (1,1)	5.684	1.326	**0.066**	**0.001**	32.305	1.758	4.479	**0.981**	0.846	-1.219	0.479	0.646	0.001	0.012	0.001	**0.078**
Exponential STAR - Tbill	4.795	1.474	-0.213	0.265	**22.945**	2.104	3.749	1.122	0.885	-0.660	0.563	0.563	0.042	0.000	**0.845**	0.001
Exponential STAR - 1-month forecast	4.942	1.335	-0.320	0.182	24.322	1.749	3.743	0.994	0.955	**-0.077**	0.542	0.563	0.006	0.010	**0.490**	**0.059**
Logistic STAR - Tbill	**4.521**	1.366	**0.056**	0.186	20.435	1.832	**3.497**	1.027	**0.500**	**0.036**	**0.667**	0.604	**0.143**	0.001	**0.989**	0.026
Logistic STAR - 1-month forecast	4.959	1.335	-0.231	0.182	24.539	1.749	3.876	0.994	0.901	-0.077	0.521	0.563	0.000	0.010	**0.481**	**0.059**
TAR - Tbill	5.204	1.388	-0.399	0.054	26.918	1.923	4.147	1.079	1.202	-0.109	0.458	0.500	0.040	0.005	0.021	0.011
TAR - 1-month forecast	5.033	1.333	-0.834	0.108	24.633	1.766	3.997	1.021	1.075	0.650	0.583	0.542	0.015	0.009	**0.175**	**0.065**
Logistic STAR GARCH(1,1) transition	5.015	1.346	-0.346	0.172	25.028	1.782	3.918	1.002	1.076	**0.043**	0.500	0.563	0.000	0.006	**0.289**	0.045
TAR with other asset	5.402	1.393	-0.593	**-0.025**	28.829	1.939	4.331	1.095	1.230	-2.851	0.396	0.583	0.062	0.002	0.002	0.010
MS Two-state Homoskedastic	**4.438**	**1.060**	-0.384	-0.033	**19.549**	**1.122**	**3.387**	**0.792**	**0.829**	-1.525	**0.750**	**0.750**	**0.192**	**0.332**	**0.596**	**0.287**
MS Two-state Heteroskedastic	**4.331**	**1.063**	-0.373	**-0.029**	**18.619**	**1.129**	**3.347**	**0.778**	**0.691**	-1.416	**0.750**	**0.750**	**0.282**	**0.315**	**0.122**	**0.440**

2003:02-2007:01

Model \ Measure	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	MAFE Stocks	MAFE Bonds	MPFE Stocks	MPFE Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression Stocks	MZ regression Bonds	MZ (p-value for Stocks	MZ (p-value for Bonds
Linear	2.854	1.421	1.245	-0.264	6.595	1.948	2.451	1.122	**1.278**	0.268	0.521	0.646	0.087	0.015	0.008	0.020
Random walk (with drift)	2.700	1.446	0.221	-0.597	7.240	**1.733**	2.176	1.112	1.734	-1.771	0.708	0.646	0.056	0.006	**0.212**	0.011
AR(1)	2.702	1.425	0.219	-0.460	7.255	1.818	2.179	**1.087**	1.772	0.565	0.708	0.625	0.004	0.001	**0.688**	0.024
Random walk (with drift and GARCH(1,1))	2.714	1.444	0.301	-0.592	7.277	1.736	2.200	1.112	1.650	-1.834	0.708	0.646	0.142	0.009	0.018	0.011
AR(1) with GARCH(1,1)	2.702	1.424	0.326	-0.484	7.195	1.793	2.182	1.087	1.701	**0.073**	0.708	0.646	0.004	0.000	**0.704**	0.025
GARCH (1,1) in mean and exogenous predictors	2.786	1.419	1.062	-0.356	6.634	1.888	2.378	1.117	1.608	**-0.012**	0.625	0.604	0.081	0.005	0.027	0.026
GARCH (1,1) in mean and exogenous predictors - t dist.	**2.550**	1.413	0.128	-0.313	6.486	1.899	**2.049**	1.116	2.255	-0.102	**0.729**	0.604	0.101	0.008	**0.943**	0.030
EGARCH (1,1) in mean and exogenous predictors	2.890	1.420	1.266	-0.341	6.748	1.900	2.435	1.113	1.507	-0.389	0.542	0.646	0.067	0.003	0.007	0.027
EGARCH (1,1) in mean and exogenous predictors- t dist.	2.667	1.417	**-0.142**	-0.209	7.091	1.964	2.107	1.114	2.397	0.558	0.708	0.604	0.034	0.014	**0.634**	0.023
TGARCH (1,1) in mean and exogenous predictors	2.704	1.414	**0.207**	-0.347	7.268	1.880	2.115	1.116	2.061	-0.089	0.688	0.625	0.024	0.003	**0.427**	0.032
TGARCH (1,1) in mean and exogenous predictors- t dist.	2.678	1.400	**0.170**	-0.299	7.145	1.871	2.084	1.111	2.177	-0.106	**0.729**	0.625	0.035	0.004	**0.507**	0.050
Recursive AR(1)	2.702	1.425	0.219	-0.460	7.255	1.818	2.179	1.087	1.772	0.565	0.708	0.625	0.004	0.001	**0.688**	0.024
Recursive AR(1) with GARCH(1,1)	2.702	1.424	0.326	-0.484	7.195	1.793	2.182	1.087	1.701	0.073	0.708	0.646	0.004	0.000	**0.704**	0.025
Linear with other asset	3.025	1.417	1.367	-0.268	7.280	1.936	2.507	1.118	1.292	0.116	0.583	0.646	0.035	0.007	0.002	0.027
Linear with other asset and GARCH (1,1)	3.024	1.411	1.325	-0.360	7.388	1.860	2.477	1.110	1.352	-0.184	0.542	0.625	0.031	0.000	0.002	0.039
Exponential STAR - Tbill	2.830	1.636	1.195	**-0.017**	6.580	2.675	2.428	1.209	1.382	-0.089	0.583	**0.667**	0.090	**0.028**	0.011	0.000
Exponential STAR - 1-month forecast	2.896	1.423	1.363	-0.237	6.528	1.969	2.469	1.134	1.676	0.526	0.542	0.583	0.097	0.009	0.003	0.021
Logistic STAR - Tbill	2.738	1.419	0.640	-0.200	7.084	1.972	2.229	1.130	2.637	1.017	0.583	0.542	0.065	0.001	**0.090**	0.030
Logistic STAR - 1-month forecast	2.898	1.423	1.238	-0.237	6.868	1.969	2.465	1.134	1.170	0.526	0.542	0.583	0.065	0.009	0.007	0.021
TAR - Tbill	2.774	1.446	1.128	**-0.195**	6.424	2.054	2.360	1.143	**1.133**	1.878	0.646	0.583	0.110	0.020	0.016	0.008
TAR - 1-month forecast	3.045	**1.392**	1.381	-0.302	7.368	1.846	2.576	1.128	1.550	-0.357	0.458	0.646	0.034	0.002	0.001	**0.069**
Logistic STAR GARCH(1,1) transition	2.922	1.413	1.178	-0.257	7.148	1.932	2.489	1.123	1.602	0.616	0.542	0.604	0.041	0.004	0.008	0.033
TAR with other asset	2.759	1.440	1.171	**-0.211**	**6.242**	2.030	2.277	1.151	1.338	1.416	0.625	0.542	**0.145**	0.007	0.008	0.013
MS Two-state Homoskedastic	**2.213**	**1.175**	0.807	-0.262	**4.248**	**1.311**	**1.918**	**0.936**	1.469	0.163	0.750	**0.708**	**0.549**	**0.378**	0.000	0.003
MS Two-state Heteroskedastic	**2.194**	**1.165**	0.817	-0.265	**4.147**	**1.287**	**1.877**	**0.934**	**1.285**	**-0.068**	**0.792**	**0.688**	**0.603**	**0.390**	0.000	0.003

Note: In all the columns, we have boldface the best three statistics (or the three highest p-values) returned across all models. In the column concerning the F-test on coefficients of the Mincer-Zarnowitz regression, a p-value equal or above a threshold of 5% indicates that the null of α=0 and β=1 cannot be rejected with a high level of confidence.

Table 7 [continued]

Sub-Sample Predictive Accuracy Measures for Stock and Bond Returns

Panel B: 12-month Horizon

1996:01-1999:09

Measure	RMSFE		Bias		Forecast Variance		MAFE		MPFE		Success Ratio		MZ regression (R-square)		MZ (p-value for ϕ_0 and ϕ_1=1)	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	4.076	1.089	0.680	-0.181	16.151	1.153	2.880	0.850	0.604	0.492	0.644	**0.756**	0.009	0.053	**0.134**	0.005
Random walk (with drift)	3.908	1.030	**-0.022**	-0.288	15.271	0.978	2.820	0.813	0.572	0.455	**0.733**	**0.756**	0.001	0.011	**0.972**	**0.130**
AR(1)	3.905	1.027	**-0.028**	-0.290	15.245	0.971	2.824	0.807	0.487	**0.453**	0.733	**0.756**	0.002	0.011	**0.982**	**0.149**
Random walk (with drift and GARCH(1,1))	3.908	1.015	**0.003**	-0.265	15.269	**0.960**	2.817	0.800	0.576	**0.446**	0.733	0.756	0.000	0.037	**0.994**	**0.141**
AR(1) with GARCH(1,1)	3.883	1.020	0.053	-0.261	15.076	0.972	2.820	0.806	0.509	**0.438**	0.733	0.756	0.015	0.005	**0.949**	**0.232**
GARCH (1,1) in mean and exogenous predictors	4.025	1.113	0.757	-0.187	15.626	1.204	2.864	0.866	0.840	0.527	0.644	0.756	0.002	0.058	**0.266**	0.002
GARCH (1,1) in mean and exogenous predictors - t dist.	3.993	1.086	0.383	-0.199	15.799	1.140	2.773	0.853	0.578	0.516	0.711	0.756	0.000	0.039	**0.390**	0.007
EGARCH (1,1) in mean and exogenous predictors	4.561	1.055	0.332	-0.059	20.697	1.111	3.165	0.837	0.743	0.468	0.600	0.711	0.025	0.000	0.001	**0.058**
EGARCH (1,1) in mean and exogenous predictors- t dist.	4.827	1.043	0.629	**-0.052**	22.904	1.084	3.207	0.811	1.115	0.530	0.667	0.733	0.005	0.001	0.000	**0.098**
TGARCH (1,1) in mean and exogenous predictors	4.095	1.100	0.720	-0.128	16.253	1.193	2.893	0.851	0.784	0.562	0.644	0.756	0.008	0.059	**0.112**	0.003
TGARCH (1,1) in mean and exogenous predictors- t dist.	4.011	1.124	0.534	-0.174	15.800	1.234	2.764	0.877	**0.367**	0.578	0.711	0.756	0.000	**0.092**	**0.323**	0.000
Recursive AR(1)	3.908	1.029	0.007	-0.282	15.271	0.979	2.821	0.812	0.579	0.458	0.733	0.756	0.001	0.019	**0.972**	**0.117**
Recursive AR(1) with GARCH(1,1)	3.909	**1.008**	0.103	**-0.055**	15.267	1.012	2.822	**0.777**	0.633	0.614	0.733	0.756	0.000	0.083	**0.981**	**0.066**
Linear with other asset	4.389	1.211	1.769	0.562	16.134	1.151	3.351	0.959	1.777	1.115	0.511	0.533	0.005	0.001	0.006	0.000
Linear with other asset and GARCH (1,1)	7.695	1.091	4.838	0.135	35.797	1.173	5.473	0.833	4.412	0.511	0.467	0.756	0.013	0.006	0.000	0.012
Exponential STAR - Tbill	4.317	1.166	2.166	0.382	13.947	1.214	3.374	0.894	1.835	0.973	0.467	0.600	0.086	0.000	0.002	0.001
Exponential STAR - 1-month forecast	4.622	1.115	2.360	0.366	15.792	1.109	3.638	0.855	1.892	0.799	0.578	0.689	0.088	0.004	0.000	0.005
Logistic STAR - Tbill	**3.624**	1.049	1.694	0.102	**10.262**	1.091	**2.734**	0.831	1.463	0.493	0.556	0.756	**0.377**	0.009	0.001	**0.061**
Logistic STAR - 1-month forecast	4.237	1.115	2.301	0.366	12.659	1.109	3.368	0.855	1.686	0.799	0.444	0.689	0.177	0.004	0.000	0.005
TAR - Tbill	4.194	1.173	2.009	0.294	13.553	1.289	3.302	0.934	2.636	0.994	0.489	0.533	0.112	0.013	0.004	0.000
TAR - 1-month forecast	4.425	1.146	1.556	0.121	17.163	1.299	3.495	0.949	0.620	0.529	0.511	0.644	0.030	0.001	0.002	0.002
Logistic STAR GARCH(1,1) transition	5.096	1.082	2.600	0.311	19.206	1.075	3.968	0.835	2.072	0.737	0.311	0.689	0.017	0.008	0.000	0.017
TAR with other asset	4.178	1.087	1.604	0.220	14.879	1.134	3.160	0.850	2.608	0.857	0.467	0.667	0.053	0.002	0.018	0.016
MS Two-state Homoskedastic	**3.186**	**0.852**	0.562	**-0.042**	**9.837**	**0.724**	**2.245**	**0.650**	**0.203**	0.580	**0.822**	0.756	**0.625**	**0.396**	0.000	0.011
MS Two-state Heteroskedastic	**3.178**	**0.863**	-0.141	-0.099	**10.081**	**0.735**	**2.308**	**0.655**	**0.318**	0.554	**0.800**	0.756	**0.454**	**0.483**	0.016	0.000

1999:10-2003:05

Measure	RMSFE		Bias		Forecast Variance		MAFE		MPFE		Success Ratio		MZ regression (R-square)		MZ (p-value for ϕ_0 and ϕ_1=1)	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	5.485	1.346	-1.526	**0.102**	27.760	1.801	4.243	**1.022**	1.314	-2.233	0.386	**0.727**	0.033	0.004	0.013	**0.277**
Random walk (with drift)	5.489	1.331	-2.207	-0.231	25.253	1.719	4.205	1.075	1.482	-3.260	0.477	0.727	0.013	0.011	0.020	**0.384**
AR(1)	5.607	1.326	-2.278	-0.253	26.248	**1.693**	4.267	1.066	1.551	-3.566	0.477	0.727	0.055	0.020	0.003	**0.378**
Random walk (with drift and GARCH(1,1))	5.483	1.338	-2.177	-0.132	25.326	1.774	4.219	1.073	1.459	-2.948	0.477	0.727	0.000	**0.022**	0.027	**0.238**
AR(1) with GARCH(1,1)	5.537	1.343	-2.246	-0.166	25.608	1.776	4.221	1.075	1.524	-3.332	0.477	0.727	0.004	0.009	0.017	**0.276**
GARCH (1,1) in mean and exogenous predictors	5.513	1.380	-1.602	0.216	27.822	1.858	4.280	1.040	1.341	-2.475	0.455	0.705	0.024	0.001	0.013	**0.104**
GARCH (1,1) in mean and exogenous predictors - t dist.	5.618	1.390	-1.933	0.212	27.826	1.887	4.430	1.059	1.502	-2.328	0.409	0.659	0.021	0.004	0.006	**0.073**
EGARCH (1,1) in mean and exogenous predictors	6.368	1.392	**-0.215**	0.267	40.505	1.866	4.811	1.060	1.406	-2.011	0.455	0.659	0.031	0.000	0.000	**0.074**
EGARCH (1,1) in mean and exogenous predictors- t dist.	5.572	1.388	-1.280	0.247	29.405	1.865	4.257	1.057	1.346	-1.863	0.500	0.636	0.014	0.000	0.010	**0.083**
TGARCH (1,1) in mean and exogenous predictors	5.583	1.373	-1.633	0.218	28.508	1.838	4.385	1.039	1.515	-2.413	0.364	0.727	0.042	0.000	0.005	**0.129**
TGARCH (1,1) in mean and exogenous predictors- t dist.	5.614	1.363	-1.867	0.196	28.038	1.819	4.392	1.028	1.362	-2.429	0.409	0.727	0.014	0.000	0.008	**0.180**
Recursive AR(1)	5.481	1.331	-2.186	-0.227	25.257	1.720	4.198	1.075	1.476	-3.240	0.477	0.727	0.013	0.014	0.021	**0.363**
Recursive AR(1) with GARCH(1,1)	5.469	**1.322**	-2.121	-0.171	25.413	1.719	4.204	1.051	1.479	-3.180	0.477	0.727	0.003	0.001	0.029	**0.625**
Linear with other asset	5.436	1.384	-0.873	0.282	28.784	1.836	4.218	1.108	**0.830**	-2.186	0.409	0.614	0.003	0.007	0.037	**0.081**
Linear with other asset and GARCH (1,1)	6.611	1.498	**0.604**	0.261	43.334	2.177	5.171	1.197	1.784	-1.284	0.432	0.591	0.039	0.011	0.000	0.003
Exponential STAR - Tbill	**4.964**	1.680	-0.613	0.437	24.268	2.631	**3.916**	1.223	1.289	-0.940	0.545	0.591	0.044	0.002	**0.703**	0.000
Exponential STAR - 1-month forecast	5.058	1.416	-1.114	0.299	24.348	1.916	3.937	1.081	1.263	-0.232	0.500	0.591	0.039	0.004	**0.352**	0.033
Logistic STAR - Tbill	5.138	1.412	-0.458	0.266	26.191	1.924	4.043	1.054	**0.975**	-0.392	0.591	0.659	**0.059**	0.003	**0.117**	0.038
Logistic STAR - 1-month forecast	5.283	1.416	**-0.509**	0.299	27.651	1.916	4.087	1.081	1.558	**-0.232**	0.545	0.591	0.001	0.004	**0.128**	0.033
TAR - Tbill	5.409	1.433	-0.956	0.220	28.346	2.007	4.308	1.078	1.574	**-0.221**	0.455	0.591	0.006	0.001	0.043	0.021
TAR - 1-month forecast	5.052	1.411	-1.241	0.248	**23.984**	1.930	4.012	1.084	1.964	0.383	**0.614**	0.614	0.063	0.003	**0.220**	0.039
Logistic STAR GARCH(1,1) transition	5.185	1.417	1.072	0.254	25.735	1.943	4.368	1.068	**0.407**	**-0.190**	0.545	0.636	0.018	0.002	**0.195**	0.034
TAR with other asset	5.620	1.430	-1.183	**0.120**	30.190	2.031	4.463	1.097	1.056	-3.314	0.432	0.659	0.028	0.001	0.005	0.023
MS Two-state Homoskedastic	**4.289**	**1.128**	-1.799	0.174	**15.162**	**1.242**	**3.359**	**0.835**	1.132	-0.876	**0.659**	**0.750**	**0.678**	**0.356**	0.000	0.048
MS Two-state Heteroskedastic	**4.427**	**1.117**	-1.249	**0.144**	**18.041**	**1.226**	**3.602**	**0.823**	1.445	-1.047	**0.636**	**0.727**	**0.386**	**0.393**	0.008	0.022

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Measure	RMSFE		Bias		Forecast Variance		MAFE		MPFE		Success Ratio		MZ regression		MZ (p-value for	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	2.803	1.374	1.030	-0.511	6.795	1.626	2.443	**1.049**	**0.283**	-1.177	0.614	0.636	0.001	0.000	0.003	0.026
Random walk (with drift)	**2.463**	1.424	**0.336**	-0.660	5.955	1.592	**2.039**	1.084	1.658	-1.759	**0.727**	0.636	0.052	0.008	**0.244**	0.005
AR(1)	2.464	1.429	**0.309**	-0.675	5.973	**1.587**	2.042	1.087	1.641	-1.589	0.727	0.636	0.002	0.001	**0.711**	0.005
Random walk (with drift and GARCH(1,1))	2.478	1.366	0.402	-0.456	5.980	1.659	2.054	1.066	1.654	-1.460	0.727	0.636	0.001	0.046	**0.571**	0.012
AR(1) with GARCH(1,1)	2.477	1.371	0.435	-0.462	5.944	1.667	2.068	1.082	1.639	-1.357	0.727	0.636	0.006	0.020	**0.518**	0.019
GARCH (1,1) in mean and exogenous predictors	2.848	1.392	1.156	-0.491	6.774	1.698	2.484	1.081	**0.197**	-0.697	0.591	0.636	0.002	0.003	0.002	0.014
GARCH (1,1) in mean and exogenous predictors - t dist.	2.707	1.386	0.718	-0.485	6.815	1.685	2.318	1.070	0.459	-0.941	0.682	0.636	0.002	0.002	0.013	0.018
EGARCH (1,1) in mean and exogenous predictors	2.909	1.401	0.833	-0.534	7.766	1.679	2.455	1.084	0.749	-0.759	0.568	0.636	0.001	0.001	0.001	0.011
EGARCH (1,1) in mean and exogenous predictors- t dist.	4.139	1.388	1.637	-0.519	14.448	1.658	3.039	1.084	0.944	-0.677	0.523	0.636	0.004	0.000	0.000	0.017
TGARCH (1,1) in mean and exogenous predictors	3.025	1.406	1.416	-0.514	7.148	1.712	2.657	1.084	**-0.040**	-0.745	0.523	0.636	0.003	0.002	0.000	0.009
TGARCH (1,1) in mean and exogenous predictors- t dist.	2.784	1.409	0.894	-0.489	6.952	1.748	2.408	1.092	0.289	-0.824	0.614	0.636	0.001	0.009	0.004	0.007
Recursive AR(1)	2.465	1.423	0.345	-0.659	5.956	1.592	2.041	1.083	1.654	-1.760	0.727	0.636	0.051	0.008	**0.243**	0.005
Recursive AR(1) with GARCH(1,1)	2.476	1.433	0.439	-0.676	5.937	1.597	2.057	1.090	1.611	-1.978	0.727	0.636	0.013	0.003	**0.458**	0.004
Linear with other asset	2.929	1.380	1.779	-0.354	5.414	1.780	2.469	1.109	0.933	-1.703	0.568	0.614	0.108	**0.065**	0.000	0.005
Linear with other asset and GARCH (1,1)	2.855	1.479	1.072	-0.525	7.003	1.910	2.380	1.127	1.210	-3.452	0.545	0.636	0.008	0.028	0.001	0.001
Exponential STAR - Tbill	2.673	1.528	1.474	**-0.068**	4.973	2.329	2.342	1.145	0.881	**-0.275**	0.568	**0.682**	**0.215**	0.030	0.000	0.000
Exponential STAR - 1-month forecast	2.735	1.393	1.521	-0.274	5.167	1.865	2.360	1.107	0.704	0.590	0.523	0.591	0.140	0.021	0.000	0.010
Logistic STAR - Tbill	2.795	1.407	1.116	**-0.222**	6.565	1.929	2.406	1.121	2.355	0.960	0.500	0.523	0.046	0.022	0.001	0.006
Logistic STAR - 1-month forecast	2.874	1.393	1.674	-0.274	5.459	1.865	2.443	1.107	0.539	**0.590**	0.523	0.591	0.092	0.021	0.000	0.010
TAR - Tbill	2.637	1.405	1.483	-0.237	**4.753**	1.919	2.297	1.111	0.644	1.504	0.614	0.568	**0.277**	0.043	0.000	0.004
TAR - 1-month forecast	3.008	**1.349**	1.678	-0.354	6.231	1.694	2.558	1.089	0.917	**-0.330**	0.477	0.636	0.028	0.003	0.000	**0.054**
Logistic STAR GARCH(1,1) transition	3.276	1.386	2.238	-0.287	5.725	1.839	2.693	1.099	0.511	0.807	0.545	0.591	0.061	0.011	0.000	0.014
TAR with other asset	2.644	1.396	1.491	**-0.255**	**4.769**	1.884	2.248	1.120	1.419	1.119	0.614	0.545	0.205	0.015	0.000	0.010
MS Two-state Homoskedastic	**2.359**	**1.099**	0.891	-0.404	4.773	**1.044**	**1.937**	**0.855**	0.790	-0.908	**0.795**	**0.659**	0.202	**0.806**	0.039	0.000
MS Two-state Heteroskedastic	**2.146**	**1.103**	**-0.068**	-0.418	**4.599**	**1.042**	**1.719**	**0.863**	0.617	-1.034	**0.795**	**0.659**	**0.232**	**0.818**	**0.963**	0.000

Note: In all the columns, we have boldface the best three statistics (or the three highest p-values) returned across all models. In the column concerning the F-test on coefficients of the Mincer-Zarnowitz regression, a p-value equal or above a threshold of 5% indicates that the null of α=0 and β=1 cannot be rejected with a high level of confidence.

Table 8

Van Dijk-Franses Equal Predictive Accuracy Tests: Symmetric Weighting Functions

Panel A: Stock Returns

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.999	0.999	0.999	0.998	0.989	0.968	0.939	0.982	0.990	0.935	0.199	0.333	0.291	0.211	0.986	0.633	0.957	**0.001**	0.069
Random walk (with drift)	0.633		0.523	0.159	0.510	**0.042**	**0.002**	**0.012**	**0.028**	0.111	**0.002**	**0.008**	**0.001**	**0.013**	**0.002**	**0.003**	**0.018**	**0.002**	**0.000**	**0.005**
AR(1)	0.795	0.864		0.292	0.497	**0.039**	**0.003**	**0.013**	**0.030**	0.118	**0.002**	**0.006**	**0.001**	**0.012**	**0.001**	**0.002**	**0.015**	**0.001**	**0.000**	**0.004**
Random walk (with drift and GARCH(1,1))	0.546	**0.036**	0.120		0.707	**0.046**	**0.003**	**0.016**	**0.040**	0.122	**0.003**	**0.009**	**0.001**	**0.016**	**0.002**	**0.003**	**0.021**	**0.003**	**0.000**	**0.006**
AR(1) with GARCH(1,1)	0.590	0.525	**0.043**	0.650		**0.044**	**0.003**	**0.013**	**0.034**	0.100	**0.003**	**0.010**	**0.001**	**0.017**	**0.002**	**0.003**	**0.021**	**0.004**	**0.000**	**0.006**
GARCH (1,1) in mean and exogenous predictors	0.122	**0.000**	0.091	**0.000**	0.191		0.641	0.586	0.778	0.865	0.482	**0.027**	0.062	0.145	**0.006**	0.364	0.145	0.194	**0.000**	**0.019**
GARCH (1,1) in mean and exogenous predictors - t dist.	0.975	1.000	0.413	1.000	0.868	0.998		0.427	0.885	0.924	0.219	0.063	**0.036**	0.107	**0.037**	0.156	0.161	0.131	**0.002**	**0.041**
EGARCH (1,1) in mean and exogenous predictors	0.834	0.791	0.709	0.807	0.774	0.845	0.759		0.899	0.911	0.282	0.078	0.051	0.104	0.069	0.303	0.195	0.184	**0.003**	0.050
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.719	0.687	0.619	0.700	0.675	0.733	0.648	0.426		0.652	**0.014**	**0.037**	**0.016**	**0.045**	**0.025**	0.108	0.097	**0.049**	**0.001**	**0.026**
TGARCH (1,1) in mean and exogenous predictors	0.860	0.680	0.243	0.898	0.570	0.964	**0.000**	0.205	0.316		**0.016**	**0.034**	**0.007**	0.076	**0.012**	**0.033**	0.087	**0.046**	**0.002**	**0.021**
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.916	1.000	0.361	1.000	0.766	0.998	0.344	0.229	0.336	0.756		0.099	**0.039**	0.121	0.074	0.407	0.236	0.239	**0.003**	**0.048**
Exponential STAR - TBILL	**0.005**	**0.006**	**0.011**	**0.006**	**0.010**	**0.003**	**0.003**	**0.011**	**0.016**	**0.007**	**0.001**		0.559	0.401	0.751	0.931	0.900	0.937	**0.000**	0.099
Exponential STAR - SRF	**0.000**	**0.000**	**0.003**	**0.000**	**0.001**	**0.000**	**0.000**	**0.014**	**0.045**	**0.001**	**0.000**	0.986		0.368	0.611	0.931	0.684	0.837	**0.015**	0.170
Logistic STAR - TBILL	**0.010**	**0.007**	**0.009**	**0.007**	**0.009**	**0.008**	**0.006**	**0.010**	**0.019**	**0.011**	**0.005**	0.118	**0.040**		0.678	0.827	0.770	0.836	0.086	0.294
Logistic STAR - SRF	**0.005**	**0.003**	**0.007**	**0.004**	**0.006**	**0.003**	**0.003**	**0.014**	**0.034**	**0.006**	**0.001**	0.781	**0.002**	0.949		0.988	0.702	0.937	**0.001**	0.076
TAR - Tbill	**0.004**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.030**	0.082	**0.003**	**0.000**	0.864	0.604	0.955	0.872		0.231	0.275	**0.001**	**0.036**
TAR - SRF	**0.011**	**0.009**	**0.016**	**0.010**	**0.014**	**0.007**	**0.007**	**0.014**	**0.032**	**0.011**	**0.003**	1.000	**0.007**	0.903	0.593	0.166		0.690	**0.000**	**0.034**
Logistic STAR - GARCH	**0.036**	**0.048**	0.057	**0.049**	0.061	**0.038**	**0.031**	**0.011**	**0.005**	**0.039**	**0.021**	0.474	0.213	0.698	0.407	0.270	0.357		**0.000**	**0.027**
MS Two-state Homoskedastic	**0.010**	**0.009**	**0.012**	**0.009**	**0.012**	**0.008**	**0.008**	**0.009**	**0.010**	**0.011**	**0.005**	**0.010**	**0.017**	0.118	**0.014**	**0.040**	**0.012**	0.087		0.914
MS Two-state Heteroskedastic	**0.010**	**0.010**	**0.014**	**0.010**	**0.013**	**0.008**	**0.008**	**0.008**	**0.009**	**0.010**	**0.005**	**0.009**	**0.016**	0.141	**0.014**	**0.036**	**0.007**	0.064	0.548	

Panel B: Bond Returns

	Linear	Random walk with drift	AR(1)	Random walk	AR(1) with GARCH(1,1)	GARCH (1,1) in mean and exogenous predictors	GARCH (1,1) in mean & exog. predictors - t dist.	EGARCH (1,1) in mean and exogenous predictors	EGARCH (1,1) in mean & exog. predictors - t dist.	TGARCH (1,1) in mean and exogenous predictors	TGARCH (1,1) in mean & exog. predictors - t dist.	Exponential STAR-Tbill	Exponential STAR-SRF	Logistic STAR-Tbill	Logistic STAR-SRF	TAR T-bill	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state Homosk.	MS Two-state Heterosk.
Linear		0.579	0.550	0.620	0.703	0.687	0.386	0.382	0.213	0.570	0.193	0.853	0.363	0.546	0.363	0.884	0.216	0.392	**0.000**	**0.000**
Random walk (with drift)	0.317		0.419	0.780	0.579	0.476	0.384	0.367	0.308	0.435	0.314	0.586	0.400	0.456	0.400	0.633	0.227	0.398	**0.000**	**0.000**
AR(1)	0.333	0.611		0.644	0.906	0.541	0.402	0.379	0.287	0.479	0.303	0.667	0.420	0.491	0.420	0.704	0.220	0.417	**0.000**	**0.000**
Random walk (with drift and GARCH(1,1))	**0.020**	0.110	0.098		0.522	0.431	0.336	0.321	0.262	0.390	0.267	0.557	0.360	0.426	0.360	0.612	0.189	0.357	**0.000**	**0.000**
AR(1) with GARCH(1,1)	**0.028**	0.180	0.167	0.885		0.371	0.231	0.218	0.145	0.314	0.156	0.563	0.283	0.389	0.283	0.632	0.126	0.268	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors	1.000	0.839	0.825	0.996	0.991		0.133	0.088	0.061	0.121	**0.032**	0.701	0.199	0.441	0.199	0.805	0.135	0.148	**0.000**	**0.000**
GARCH (1,1) in mean and exogenous predictors - t dist.	0.980	0.806	0.792	0.993	0.986	0.070		0.434	0.138	0.712	0.119	0.848	0.495	0.583	0.495	0.875	0.222	0.501	**0.000**	**0.000**
EGARCH (1,1) in mean and exogenous predictors	0.843	0.782	0.768	0.989	0.982	0.263	0.361		0.240	0.811	0.268	0.818	0.554	0.631	0.554	0.882	0.229	0.571	**0.001**	**0.000**
EGARCH (1,1) in mean and exogenous predictors- t dist.	0.595	0.681	0.666	0.952	0.928	0.103	0.154	0.140		0.878	0.534	0.880	0.732	0.709	0.732	0.910	0.320	0.762	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors	0.996	0.875	0.868	0.999	0.997	0.614	0.808	0.798	0.877		0.080	0.765	0.297	0.509	0.297	0.860	0.180	0.250	**0.000**	**0.000**
TGARCH (1,1) in mean and exogenous predictors- t dist.	0.981	0.885	0.878	0.998	0.996	0.773	0.897	0.840	0.884	0.895		0.884	0.751	0.700	0.751	0.925	0.315	0.784	**0.000**	**0.000**
Exponential STAR - TBILL	0.437	0.611	0.601	0.908	0.880	**0.000**	**0.023**	0.309	0.417	**0.041**	**0.000**		0.151	0.300	0.151	0.615	0.148	0.162	**0.000**	**0.000**
Exponential STAR - SRF	0.253	0.416	0.409	0.587	0.567	0.104	0.131	0.143	0.173	0.091	0.094	0.265		0.616	0.251	0.937	0.238	0.514	**0.001**	**0.001**
Logistic STAR - TBILL	0.260	0.400	0.395	0.548	0.528	0.129	0.150	0.165	0.196	0.126	0.122	0.224	0.412		0.384	0.828	0.223	0.388	**0.002**	**0.002**
Logistic STAR - SRF	0.253	0.416	0.409	0.587	0.567	0.104	0.131	0.143	0.173	0.091	0.094	0.265	0.949	0.588		0.937	0.238	0.514	**0.001**	**0.001**
TAR - Tbill	0.655	0.671	0.667	0.795	0.794	0.517	0.550	0.586	0.663	0.496	0.455	0.676	0.923	0.959	0.923		0.082	0.063	**0.001**	**0.001**
TAR - SRF	0.113	0.217	0.219	0.352	0.328	0.076	0.092	0.088	0.098	0.083	0.083	0.095	0.104	0.253	0.104	**0.032**		0.771	**0.001**	**0.001**
Logistic STAR - GARCH	0.233	0.395	0.388	0.564	0.543	0.096	0.119	0.121	0.146	0.084	0.088	0.242	0.345	0.532	0.345	0.079	0.897		**0.001**	**0.001**
MS Two-state Homoskedastic	**0.002**	**0.002**	**0.003**	**0.007**	**0.008**	**0.002**	**0.003**	**0.004**	**0.004**	**0.004**	**0.003**	**0.001**	**0.010**	**0.020**	**0.010**	**0.011**	**0.009**	**0.012**		0.503
MS Two-state Heteroskedastic	**0.003**	**0.003**	**0.003**	**0.008**	**0.009**	**0.003**	**0.004**	**0.005**	**0.005**	**0.004**	**0.004**	**0.001**	**0.015**	**0.025**	**0.015**	**0.015**	**0.013**	**0.017**	1.000	

Note: The table presents p-values for Diebold and Mariano's test of no differential in predictive accuracy when loss function differences are weighted as proposed by van Dijk and Franses (2003). Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report vDF p-values under a symmetric, square loss function for a 1-month forecast horizon; below the main diagonal, we report vDF p-values for a 12-month horizon.