Non-Linear Predictability in Stock and Bond Returns: When and Where Is It Exploitable?

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Abstract

We systematically examine the comparative predictive performance of a number of alternative non-linear models for stock and bond returns in the G7 countries. Besides, Markov switching, threshold, and smooth transition regime switching (predictive) regression models, we also estimate univariate models in which conditional heteroskedasticity is captured through TARCH, GARCH and EGARCH models and ARCH-in mean effects appear in the conditional mean. Although we fail to find a consistent winner/out-performer across all countries and asset markets, it turns out that capturing non-linear effects is of extreme importance to improve forecasting performance. U.S. and U.K. asset return data are "special" in the sense that good predictive performance seems to loudly ask for non-linear effects, especially of the Markov switching type. Although occasionally also stock and bond returns from other G7 countries appear to require non-linear modeling (especially of TAR and STAR type), data from France, Germany, and Italy express interesting predictive results on the basis of simpler benchmarks. U.S. and U.K. data are also the only two data sets in which we find statistically significant differences between forecasting models.

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We systematically examine the comparative predictive performance of a number of alternative non-linear models for stock and bond returns in the G7 countries. Besides, Markov switching, threshold, and smooth transition regime switching (predictive) regression models, we also estimate univariate models in which conditional heteroskedasticity is captured through TARCH, GARCH and EGARCH models and ARCH-in mean effects appear in the conditional mean. Although we fail to find a consistent winner/out-performer across all countries and asset markets, it turns out that capturing non-linear effects is of extreme importance to improve forecasting performance. U.S. and U.K. asset return data are "special" in the sense that good predictive performance seems to loudly ask for non-linear effects, especially of the Markov switching type. Although occasionally also stock and bond returns from other G7 countries appear to require non-linear modeling (especially of TAR and STAR type), data from France, Germany, and Italy express interesting predictive results on the basis of simpler benchmarks. U.S. and U.K. data are also the only two data sets in which we find statistically significant differences between forecasting models.

1. **Introduction**

The possibility that macroeconomic aggregates may predict the evolution of asset prices has been attracting the attention of a wide range of researchers in economics and finance at least since the late 1970s. Against the background of the efficient market hypothesis (EMH) developed in the 1960s and 70s (for which asset prices should follow a random walk or anyway be unpredictable given current information), the existence of statistically detectable predictability patterns has been considered interesting not only for its intrinsic usefulness in asset pricing and portfolio management, but also because a reconciliation between the EMH and the predictive power of macroeconomic variables was perceived as a high-priority research question. Therefore a remarkable bulk of empirical evidence on such predictability relationships linking asset returns and macroeconomic factors has been cumulating, although it is now clear that the EMH may be consistent with predictability.[1]

Recent years have seen this debate develop in two distinct directions. On the one hand, considerable resources have been invested into finding the most accurate and useful - for out-of-sample goals, for instance in portfolio choice applications - prediction variables. On the other hand, recently considerable interested has concerned the possibility that - even given traditional sets of prediction variables (such as those originally proposed by Chen, Roll, and Ross, 1986, and Fama and French, 1989) - predictability patterns may take a non-linear structure. This research has been conducted across a range of financial assets, including both interest rate dynamics, for which major examples include Balke and Fomby (1997), Enders and Granger (1998), Franses and van Dijk (2000), Enders and Siklos (2001) and McMillan (2004); and equity returns, Martens, Kofman and Vorst (1998), Perez-Quiros and Timmermann (2000), Leung, Daouk and Chen (2000), McMillan (2001, 2003, 2005), Maasoumi and Racine (2002) and Shively (2003).

The general consensus from this literature is that non-linear models do provide a richer understanding of the in-sample dynamics of variables of interest; however, there is less certainty as to whether such models provide for a forecasting improvement. Indeed Clements and Hendry (1998) provide an analysis of forecasting with non-linear models and discuss reasons why a superior in-sample fit may not translate into a superior out-of-sample performance (see also Brooks, 1997 and de Gooijer and Kumar, 1992). Various reasons have been provided for such a failure including a lack of non-linearity in the out-of-sample portion of the data, the use of an inappropriate metric against which to measure forecasting performance, and that the non-linear model is in some sense 'wrong', i.e. sample specific and prone to time variation in the nonlinear dynamics (see, for examples of these, Diebold and Nason, 1990; Clements and Smith, 1999; Dacco and Satchell, 1999). Nevertheless, a true test of the usefulness of a model in describing data, and therefore informing market agents or policy makers, must be its ability to forecast.

[1] In synthesis, the random walk actually obtains only under special assumptions or after appropriately scaling the asset prices. More generally, the EMH simply implies the existence of a relationship between asset returns and all variables that contain information on the fundamental pricing operator (the stochastic discount factor). Various papers study whether arbitrage pricing theory (APT) can employ macroeconomic variables as risk factors. These studies focus on a contemporaneous relation between stock returns and macroeconomic variables. Examples include Chen, Roll, and Ross (1986) and Burmeister and McElroy (1988) among others. Campbell, Lo, and Mackinlay (Chapters 2 and 6, 1997) survey these literatures.

The objective of our paper is to perform a systematic evaluation of whether, when, and where non-linear econometric models may provide accurate forecasts. We do this by forecasting monthly stock and bond returns in the G7 countries and using - as a baseline linear framework in the absence of any non-linear structure - a standard set of macroeconomic variables widely used in the empirical finance literature (change in short-term interest rates, the term spread, the dividend yield, inflation, rate of growth of industrial production, the change in the unemployment rate, the rate of growth in oil prices, and the change in the log-effective exchange rate). Since our goal does not consist in showing that any peculiar kind of non-linear econometric framework is optimal, in this paper we consider a wide range of econometric frameworks, from standard Markov switching predictive regressions, threshold predictive regressions, to smooth transition predictive regressions. Of course, we oppose this relatively large set of non-linear models to a number of commonly used benchmarks (besides the obvious, i.e., a simple, homoskedastic predictive regression): the random walk model with drift and simple autoregressive models.

Besides returning to the always important question on whether non-linear models may improve applied forecasting performance in finance, our paper pursues one additional goal. We ask whether it may be important - again, in terms of out-of-sample predictive accuracy - to capture conditional heteroskedasticity and use classical "ARCH-in mean" effects to create a linkage between conditional mean functions useful in forecasting and the well-known conditional heteroskedastic function often discussed in empirical finance. We find two important results. First, U.S. and U.K. asset return data (and, to a lesser extend, Canadian) appear to be "special" in the sense that good predictive performance seems to loudly ask for modeling nonlinear effects, especially of the Markov switching type. Although occasionally also stock and bond returns from other G7 countries appear to require non-linear modeling (especially of TAR and STAR type), data from France, Germany, and Italy may often express interesting predictive results on the basis of rather simple benchmarks, at times a naive linear homoskedastic model. Second, U.S. and U.K. data appear once more "special" because they are the only two countries in which the data are rich enough to allow us to test and find statistically significant difference between forecasting models.

The paper is structured as follows. Section 2 gives a quick literature review that helps focussing on the goals and limitations of our exercise. Section 3 describes the data. Section 4 gives an introduction to estimation, inference, and forecasting in a range of econometric frameworks, including many non-linear econometric models. Section 5 explains how the forecast results in our application are evaluated and compared. In particular, we introduce a number of statistical tests used to assess whether the data reveal any statistically significant evidence of over-performance of any model when compared with its competitors. Section 6 presents the results, distinguishing between general implications of our massive forecasting experiments and country- and asset-specific results of some relevance in applied terms. Section 7 concludes. One appendix provides details on the data used in the paper, their construction, and their original sources.

2. **Review of the Literature**

There is a wide literature which examines the ability of macroeconomic variables to predict future asset returns. Early work (Bodie, 1976; Fama and Schwert, 1977; Jaffe and Mandelker, 1976; Nelson, 1976) focuses on the relationship between returns and inflation while Fama (1981) extends the analysis to investigate the correlation between stock returns and expected and unexpected inflation in the US, showing that the observed negative relation is a 'proxy effect' for more fundamental relationships between stock returns and real activity. Geske and Roll (1985) offer a supplementary explanation that stock prices signal changes in expected inflation because money supply responds to changes in expected real activity while James, Koreisha and Partch (1985) find strong links between stock returns, real activity and money. These US findings are largely reinforced by the multi-country studies of Mandelker and Tandon (1985) and Kaul (1987). Chen, Roll and Ross (1986) consider a wider set of macroeconomic variables, identifying the importance of the term spread, oil prices and industrial production growth in explaining stock return behavior.[2] Cutler, Poterba and Summers (1989) and Balvers, Cosimano and McDonald (1990) provide further evidence of the forecasting power of industrial production. Evidence of the role of the dividend yield and the term spread in determining stock prices is provided by Fama and French (1988, 1989) while interest rates are commonly adopted as predictor variables (Campbell, 1987; Hodrick, 1992; Ang and Bekaert, 2007) and Boyd, Hu and Jagannathan (2005) demonstrate the ability of the unemployment rate to predict returns. Asprem (1989) documents a positive relationship between stock returns and real activity using data from 10 European countries in addition to finding support for money supply, interest rate and exchange rate variables. The strength of the relation between stock returns and real activity or industrial production is further enhanced by the findings of Fama (1990) and Schwert (1990). Additionally, Cheung and Ng (1998) provide evidence of long-run relationships between the stock market and the macroeconomy for five stock markets (the US, Canada, Germany, Italy and Japan). The long run relationships provide additional explanatory power for stock returns to that contained in dividend yields, default and term spreads and future GNP growth.

Recently Rapach, Wohar and Rangvid (2005) examine the predictability of stock returns using macroeconomic variables in an international sample. Much of this literature examines the relationships in a linear framework, McQueen and Roley (1993) argue that failure to identify the influence of macroeconomic variables on asset returns may be due to the use of such constant coefficient/time invariant models. Flannery and Protopapadakis (2002) examine the relationship between stock returns and macroeconomic variables (announcements) in a GARCH framework, demonstrating that price and money measures, and unemployment had significant impacts while output and industrial production were insignificant. However recent attention has moved to the testing and estimation of nonlinear dynamics is returns. Recent evidence has shown that regime switching models that account for different phases in the business cycle are quite suc-

[1]The literature discussed here is by no means exhaustive, it merely provides relevant examples.

[2]These findings are not confined to the US, e.g. Clare and Thomas (1994) investigate a wide range of factors in the UK reporting broadly consistent findings with those of Chen, Roll and Ross (1986).

cessful in this regard, see Schaller and van Norden (1997), Perez-Quiros and Timmermann (2000), Ang and Bekaert (2002), Kanas (2003) and Guidolin and Timmermann (2003, 2005). These studies adopt the Markov switching approach of Hamilton (1989). In particular, Guidolin and Ono (2006) document non-linearity in the relationship between US excess stock and bond returns and macroeconomic predictor variables, finding evidence of multiple regimes and time varying covariances and demonstrate the superior out-of-sample performance of such a model to a comparable linear VAR.

An alternative approach to model nonlinearity is to adopt the threshold and smooth transition models, see Teräsvirta (1994), van Dijk, Teräsvirta and Franses (2002) and Teräsvirta (2004). A number of studies have applied these type of approaches to modeling stock returns, see Sarantis (2001), Mcmillan (2001), Bradley and Jansen (2004) and Bredin and Hyde (2005, 2008). Sarantis (2001) employs smooth transition autoregressive (STAR) models to investigate cyclical behavior of stock returns in the G7. The estimated models suggest that stock price behavior is characterized by asymmetric cycles with relatively slow rates of transition between regimes and out-of-sample forecasts from the models outperform a random walk. Mcmillan (2001) finds evidence in the US of a nonlinear relationship between stock market returns and macroeconomic and financial variables. Using a two regime STAR model, the results shows that while interest rates are important determinants in both regimes, the macroeconomic series (unemployment) only explains stock returns in one regime. Bredin and Hyde (2008) investigate the influence of global (U.S.) and regional (U.K. and Germany) macroeconomic and financial variables on equity returns in two small open markets (Ireland and Denmark). They identify that US stock returns, changes in US interest rates and changes in oil prices are important determinants of regime change. Bradley and Jansen (2004) model stock return and industrial production using various nonlinear models including STAR, reporting that out-of-sample forecasts from a linear model do as well or better than the forecasts from the STAR model. While both Mcmillan (2001) and Bredin and Hyde (2008) report that the in-sample performance and out-of-sample forecasts of the smooth transition regressions are superior to the linear specifications.

3. **Data**

We use monthly data on asset returns and a standard range of predictive variables for the period 1979:02 - 2007:01. The data are obtained from Datastream and Global Financial Database and concern the financial returns and macroeconomic variables for the G7 countries. In particular, data concern stock (r_t^{stock}) and bond (r_t^{bond}) returns, the log-dividend yield (dy_t), changes in the short-term interest rate (3 month Treasury bill, Δi_t), the term spread ($Term_t$) defined as the difference between long- (10 year) and the short-term (3 month) 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 all seasonally adjusted. A Data Appendix gives details on the exact sources employed in the paper and on their mnemonics.

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 vary from 6.34% in the case of Germany to 15.47% in the case of Italy; volatilities vary between 14.25% per year in the case of the United States to 23.92% of Italy. The values for the U.S. and the U.K. are the ones typically debated, i.e. on average 13-14% per year vs. annualized volatilities of 14-16%. A less well-known feature of the financial data is that in the G7 and between 1979 and 2007 realized bond returns tend to be an average comparable to stock returns and yet display considerably lower volatilities. Annualized mean bond returns vary between 5.55% for Japan to 12.52% for Italy; bond volatilities go from 5.16% for the U.K. to 9.54% for the U.S.[3] Both stock and bond returns display substantial deviations from normality, as highlighted by the rejections of the null of zero skewness and zero excess kurtosis underlying the Jarque-Bera's test. In particular, stock returns systematically display negative skewness (Italy is the only exception) and high kurtosis, easily in double digits. The features are similar for bond returns, although in this case both cases of positive and negative skewness appear.

Although it is difficult to comment in any systematic way on the properties of predictor variables, Table 1 also shows a few interesting features. Mean and median changes in short term rates are non-positive, which is consistent with the fact that most of our sample period is dominated by declining short-term interest rates after the peaks reached in the early 1980s. The term spread is everywhere positive on average (only the median value of the U.K. represents an exception) and ranges from 64 basis points in the U.K. to 2046 b.p. in the U.S. The CPI inflation rate corresponds to general perception that divides low-inflation countries (Germany and Japan with mean inflation rates of 1-2 percent per year) from high-inflation countries (essentially Italy and the U.K. with inflation rates of 5-6 percent per annum). Finally, a substantial majority of the series under investigation displays strong departures from normality. As stressed in many papers (see e.g., Timmermann, 2000) using regime switching models (hence, mixtures of Gaussian densities) readily delivers distributions which are capable to capture such non-normal features.

4. **The Forecasting Models**

Although most (or all) the econometric models employed in this paper to forecast stock and bond returns have already been largely investigated (usually on a one-by-one basis and on heterogeneous asset returns data sets) in the literature, it is useful to briefly but systematically introduce and review them before proceeding to estimation and to the recursive production of pseudo-out-of-sample forecasts. For expositional clarity, we group the models in large "families" then providing details on the specific versions that have recursively estimated in this paper.

[3]The fact that Italy tends to display systematically high nominal average returns should not be a surprise in the light of the higher average inflation rate in Italy over the sample period. For instance, annualized mean and volatility of real stock returns are 9.10 and 13.24 percent for the U.S., vs. 9.46 and 22.46 percent for Italy. A similar effect concerns bond returns.

4.1. *Linear Models*

Our baseline forecasting model is obviously represented by a simple linear regression framework that projects asset returns at time $t+h$ ($h \geq 1$) on the macroeconomic variables in the time t information set:

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

where j equals to either stocks (s) or bonds (b), $\mathbf{X}_t \equiv [r^j_t \ dy_t \ \Delta i_t \ TERM_t \ \Delta s_t \ \Delta oil_t \ \pi_t \ \Delta ip_t \ \Delta u_t]'$, ϵ^j_{t+h} is a martingale difference sequence. Notice that from the formal equation we have omitted a subscript or superscript to denote the country/markets under investigation, in the attempt not to make the already involved notation more heavy than one actually needs. However, the unknown parameter vectors α^j_h and β^j_h remind us of the forecast horizon implicit in the predictive regression estimated as well as of the asset market under analysis, whether stock or bond. To pick up potential autoregressive effects, (1) includes in the vector of predictors $\mathbf{X}_t$ also the current, time t value of the asset return, r^j_t. Of course, linear models such as (1) have received tremendous attention in the existing literatures, both in the empirical finance and statistical forecasting camps. As discussed in the Introduction, the two main hypothesis tested in this paper are: (i) whether modeling conditional heteroskedastic effects (especially when allowed to affect forecasts of the conditional mean) may improve some dimensions of the general notion of prediction accuracy; (ii) whether non-linearities of different type and structure may similarly improve forecasting performance. The next three groups of forecasting models consist of modifications and augmentations of (1) that allow us to deal with questions (i)-(ii).

4.2. *ARCH-in Mean Models*

These group of prediction models correspond to (1) when the linear regression is simply augmented by allowing time-varying predictions of asset return volatility (standard deviation) to affect conditional mean predictions. Time-varying predictions of the variance are computed from estimated univariate ARCH models, in line with the bulk of the empirical finance literature:

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

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 define as m the number of variables collected by $\mathbf{X}_t$, i.e. the number of columns of this $T \times m$ matrix. For instance, the simplest case is when the conditional heteroskedasticity model is simply set to be of a Gaussian GARCH(1,1) type,

$$h^j_{t+1} = \omega^j + \zeta^j(\eta^j_t)^2 + \theta^j h^j_t, \tag{3}$$

in which ϵ^j_t is assumed to be conditionally normal, $\epsilon^j_t|\mathcal{I}_t \sim N(0, h^j_t)$, so that η^j_t is standard normal, and $\hat{\sigma}^j_{t+1} = \sqrt{\hat{\omega}^j + \hat{\zeta}^j(\eta^j_t)^2 + \hat{\theta}^j h^j_t}$; $\mathcal{I}_t$ denotes the information set at time t.[4] Notice that this framework projects

[4]When $h \geq 2$, the multi-period forecasts are derived by iterating on the basic conditional heteroskedastic equation; for instance, $\hat{\sigma}^j_{t+2} = \sqrt{\hat{\omega}^j + (\hat{\theta}^j)^2(\hat{\sigma}^j_{t+2})^2}$. Therefore while the linear forecasts are derived using the direct prediction method that

asset returns on time t forecasts of their volatility that refer to the same point in the future. However, this is completely consistent because we can express $\hat{\sigma}^j_{t+h}$ as $\sigma^j_{t,t+h}(\mathcal{I}_t)$, then (2) reads as a standard prediction model,

$$r^j_{t+h} = \alpha^j_h + (\beta^j_h)'\mathbf{X}_t + \gamma\sigma^j_{t,t+h}(\mathcal{I}_t) + \epsilon^j_{t+h} \quad \epsilon^j_{t+h}|\mathcal{I}_t \sim F(0, h^j_{t+h}; \nu),$$

where $F(0, h^j_{t+h}; \nu)$ is a specified parametric distribution function (with parameters ν). In fact, the Gaussian GARCH(1,1) model is just one of the six cases we consider in this paper:

1. Linear Gaussian GARCH(1,1)-in mean model (see above);

2. Linear t-student GARCH(1,1)-in mean model, i.e. (2)-(3) and $F(0, h^j_{t+h}; \nu)$ t-Student, while ν the number of degrees of freedom.

3.-4. Linear EGARCH(1,1)-in mean model, i.e., (2) with

$$\ln h^j_{t+1} = \omega^j + \zeta^j\{(|\eta^j_t| - E[\eta^j_t]) + \delta^j\eta_t\} + \theta^j \ln h^j_t,$$

with η^j_t either standard normal or t-Student with ν the number of degrees of freedom.

5.-6. Linear Threshold GARCH(1,1)-in mean model, i.e., (2) with

$$h^j_{t+1} = \omega^j + \zeta^j(\eta^j_t)^2 + \theta^j h^j_t + \lambda^j I^j_t \epsilon^j_t \qquad I_t = \begin{cases} 1 & \text{if} \quad \epsilon^j_t \leq 0 \\ 0 & \text{if} \quad \epsilon^j_t > 0 \end{cases},$$

with η^j_t either standard normal or t-Student with ν the number of degrees of freedom. This is a very interesting model because it mixes a linear structure in the conditional mean equation (2) with the presence of non-linear effects in the equation for the conditional variance. We shall return on the meaning and importance of such non-linear effects in higher order moments for our research design.

4.3. *Markov Switching Models*

The popular press often acknowledges the existence of financial market states by referring to them as "bull" and "bear" markets. Here we consider that the predictive relationship between stock and bond returns and a set of macroeconomic variables may depend on a set of unobservable states that follow a first-order Markov process:

$$r^j_{t+h} = \alpha^j_{h,S_t} + (\beta^j_{h,S_t})'\mathbf{X}_t + \epsilon^j_{t+h} \quad \epsilon^j_{t+h}|\mathcal{I}_t \sim N(0, h^j_{t+h,S_t}), \tag{4}$$

where both the constant α^j_{h,S_t}, the vector of regression coefficients β^j_{h,S_t}, and the residual 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. The presence of heteroskedasticity is allowed in the form of regime-specific variances. Crucially, S^j_t is never observed and the nature of the state at time t may at most be inferred (filtered) by the

simply projects time $t+h$ asset returns on time t variables, ARCH-in mean forecasts are derived combining the direct (on the conditional mean) and indirect method.

econometrician using the history of asset returns. Similarly to most of the literature on regime switching models in finance (see e.g. Guidolin and Timmermann, 2006) and econometrics (see e.g., Hamilton, 1989), we assume that S_t^j follows a first-order Markov chain. Moves between states are assumed to be governed by a constant transition probability matrix, $\mathbf{P}^j$, with generic element p_{il}^j defined as

$$\Pr(s_{t+1}^j = l | s_t^j = i) = p_{il}^j, \quad i, l = 1, .., k, \tag{5}$$

i.e. the probability of switching to state i between t and $t+1$ given that at time t the market is in state l. While we allow for the presence of regimes, we do not exogenously impose or characterize them, consistently with the true unobservable nature of the state of markets in real life. In particular, and consistent with most of the existing literature both in empirical finance and in forecasting, in this paper we impose and estimate simple two-state predictive regressions in which $k = 2$. As a result,

$$\begin{array}{ll} \Pr(s_{t+1}^j = 1 | s_t^j = 1) = p_{11}^j & \Pr(s_{t+1}^j = 2 | s_t^j = 1) = 1 - p_{11}^j \\ \Pr(s_{t+1}^j = 1 | s_t^j = 2) = 1 - p_{22}^j & \Pr(s_{t+1}^j = 2 | s_t^j = 2) = p_{22}^j \end{array}$$

and (4) can be re-written as:

$$r_{t+h}^j = [I_t \alpha_{h,1}^j + (1 - I_t)\alpha_{h,2}^j] + [I_t \beta_{h,1}^j + (1 - I_t)\beta_{h,2}^j]' \mathbf{X}_t + \epsilon_{t+h}^j \quad \epsilon_{t+h}^j | \mathcal{I}_t \sim N(0, I_t h_{t+h,1}^j + (1 - I_t) h_{t+h,2}^j),$$

where

$$I_t = \begin{cases} 1 & \text{if} \quad S_t^j = 1 \\ 0 & \text{if} \quad S_t^j = 2 \end{cases}$$

From an economic viewpoint, the assumption of two-state Markov switching dynamics implies that in each country, financial markets may switch between two alternative predictive frameworks,

$$\begin{aligned} r_{t+h}^j &= \alpha_{h,1}^j + (\beta_{h,1}^j)' \mathbf{X}_t + \epsilon_{t+h}^j \quad \epsilon_{t+h}^j | \mathcal{I}_t \sim N(0, h_{t+h,1}^j) \\ r_{t+h}^j &= \alpha_{h,2}^j + (\beta_{h,2}^j)' \mathbf{X}_t + \epsilon_{t+h}^j \quad \epsilon_{t+h}^j | \mathcal{I}_t \sim N(0, h_{t+h,2}^j). \end{aligned}$$

This means 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. For instance, the time t rate of growth of industrial production may impact our forecasts of bond returns only when the bond market is in a bull state of high returns caused by declining monetary policy easing; the story would then be that in such a regime, good news on the real production front may indicate that in the immediate future monetary policy may turn no longer accommodative, causing IP growth to forecast lower bond returns in this state only. This type of discontinuities echo the switching effect in predictive relationships involving stock and bond returns since the seminal paper by Pesaran and Timmermann (1995). 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. For instance, in our example above, the data may reveal that while in a bull regime high IP growth forecasts lower future bond returns for the reasons illustrated, on the opposite in a bear state, high IP growth may forecast higher bond returns if a flattening of the yield curve predicted within the business cycle justifies expectations of lower future short term rates. Clearly, the switching implied by (4) defines a powerful pattern of non-linear predictability.

(4) nests several alternative frameworks as special cases. If there is a single market regime, we obtain the linear predictive regression in (1) that is commonly used in most empirical finance literature.[5] When $k = 1 = m$ with $\mathbf{X}_t$ that reduces to r_t^j, (4) reduces to a simple autoregressive framework that we shall use as a benchmark. Finally, when $k = 1$ and $m = 0$, (4) originate a simple random walk with drift that we shall use as a benchmark. Another interesting distinction concerns the case of $h_{t+h,1}^j = h_{t+h,2}^j$ – i.e., when the variance becomes independent of the regime, which originates a simple MS model in which the switching only concerns the predictive regression component – vs. the heteroskedastic case of $h_{t+h,1}^j \neq h_{t+h,2}^j$. We name the last case MSH to indicate that the Markov switching dynamics also involves the variance.

Although highly flexible, Markov switching models often imply a need to estimate a relatively large number of parameters. For instance, (4) implies $k(m+2)+k(k-1)$ parameters, where m is the number of predictive regressors specified within a linear framework. In our application, with $m = 9$, this implies the need to estimate $[11 + (k-1)]k$ parameters with the result that with the quantity of data available to us for the G7 countries it appears that $k = 2$ (i.e., 24 parameters) imposes a reasonable upper bound to the difficulty of the estimation problem. In fact, our approach imposes further implicit restrictions. First, and in a manner consistent with the approach adopted for other families of models, we estimate the properties of the Markov state separately for stock and bond markets in each country (hence the notation S_t^j). As argued in Guidolin and Timmermann (2006, 2008) it may be sensible to jointly estimate the latent market state using data from both stock and bond markets. However, since our focus is on the predictive performance and inherently univariate, this seems to be appropriate. Second, when the variance is allowed to depend on the state, we allow both the conditional mean framework and the conditional variance to be governed by a single state variable, S_t^j. This matches our desire to investigate whether capturing non-linearities in both the first and second moments and in explicitly allowing – although through the definition of the state only – the conditional variance to affect conditional mean may lead to improvements in forecasting accuracy.

4.4. *Threshold and Smooth Transition Regime Switching Models*

Although heavily employed so far in the empirical finance literature, Markov switching models trade-off their flexibility – incarnated by the fact that the switching variable remains unobservable and is assumed for simplicity to consist of a first-order Markov chain – with a number of difficulties of interpretation of the resulting state process. Given their popularity in applied econometrics, we therefore expand the families of non-linear models to include 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

[5] The i.i.d. Gaussian model – also often adopted as a benchmark in the portfolio choice literature (see e.g. Barberis, 2000) – obtains instead assuming $k = 1$ and $p = 0$.

on whether the transition variable is above or below the transition (or threshold) point:

$$
\begin{aligned}
r^j_{t+h} &= [I_t\alpha^j_{h,1} + (1-I_t)\alpha^j_{h,2}] + [I_t\beta^j_{h,1} + (1-I_t)\beta^j_{h,2}]'\mathbf{X}_t + \epsilon^j_{t+h} \quad \epsilon^j_{t+h} \sim IIN(0, h^j_h) \\
I_t &= \begin{cases} 1 & \text{if} \quad g(\mathbf{X}_t) > c \\ 0 & \text{if} \quad g(\mathbf{X}_t) \le c \end{cases},
\end{aligned} \tag{6}
$$

i.e. each of the two regimes applies in dependence on whether $g(\mathbf{X}_t)$ exceeds or not a threshold c (to be estimated), where $g : \mathcal{R}^m \to \mathcal{R}$, a function that converts the current, time values of the predictors in $\mathbf{X}_t$ into a value to be compared with the threshold c. Of course, when the function $g(\cdot)$ reduces to a selector that "extracts" one variable from $\mathbf{X}_t$, then the regime is defined simply on the basis of the extracted variable. Notice that our baseline TAR model is homoskedastic, i.e., governed by independently and identically normally distributed random shocks. For instance, the logic of such a non-linear model may be as follows: high IP growth has a negative effect on future bond returns as long as monetary policy is in a tightening cycle, as revealed by the fact that short-term rates are increasing by an amount exceeding some (endogeneously determined) threshold c; otherwise high IP growth rates will forecast positive future bond returns. This means that here $g(\cdot)$ simply selects Δi_t off $\mathbf{X}_t$ and that the coefficient in $\beta^{bond}_{h,1}$ related to the effects of IP growth is negative, while the similar coefficient in $\beta^{bond}_{h,2}$ is positve.

In addition to TAR models we also consider smooth transition regression models (STR, for a general discussion see Teräsvirta, 1998). Whilst the TAR model imparts an abrupt non-linear behaviour depending on whether the threshold variable is above or below the threshold value, the smooth-transition variant allows for possible gradual movement between regimes, and is able to capture two types of adjustment. First, the parameters of the model change depending upon whether the transition variables is above or below the transition value (essentially, this generalizes the TAR model). Second, the parameters of the model change depending upon the distance between the the transition variable and the transition value. The general STR model is given by:

$$
r^j_{t+h} = \alpha^j_{h,1} + (\beta^j_{h,1})'\mathbf{X}_t + [\alpha^j_{h,2} + (\beta^j_{h,2})'\mathbf{X}_t]F(\mathbf{e}'_i\mathbf{X}_t) + \epsilon^j_{t+h} \quad \epsilon^j_{t+h} \sim IIN(0, h^j_h), \tag{7}
$$

where $0 \le F(\mathbf{e}'_i\mathbf{X}_t) \le 1$ 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. Clearly, different values of i in the set 1, 2, ..., m correspond to alternative choices of the transition variable. In the same way, one may think of generalizing $F(\mathbf{e}'_i\mathbf{X}_t)$ to $F(g(\mathbf{X}_t))$, where $g : \mathcal{R}^m \to \mathcal{R}$, a function that converts the current, time values of the predictors in $\mathbf{X}_t$ into a value to be fed into the transition function. The smooth transition is perhaps theoretically more appealing over the simple threshold models that impose an abrupt switch in parameter values because only if all traders act simultaneously will this be the observed outcome. For a market of many traders acting at slightly different times a smooth transition model is more appropriate. For instance, it may be true that high IP growth has a negative effect on future bond returns only when monetary policy is strongly tightening, meaning that $\mathbf{e}'_i\mathbf{X}_t$ selects Δi_t and that $F(\mathbf{e}'_i\mathbf{X}_t) \simeq 1$ for very high values of Δi_t; at the same it may be sensible that high IP growth rates forecast positive future bond returns only for extremely negative values of Δi_t, for which $F(\mathbf{e}'_i\mathbf{X}_t) \simeq 0$. In intermediate situations of $\Delta i_t \simeq 0$, $F(\mathbf{e}'_i\mathbf{X}_t)$ could take intermediate values so that the effect of IP growth on r_{t+h}^{bond} will be captured by a weighted combination of elements in $\beta_{h,1}^{bond}$ and $\beta_{h,2}^{bond}$.

The STR model allows different types of market behaviour 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 behaviour depending on whether the transition variable is above or below the transition value and is given by the following, where the full model is referred to as the Logistic STR (or LSTR) model:

$$F(\mathbf{e}_i'\mathbf{X}_t) = \frac{1}{1+\exp(-\rho(\mathbf{e}_i'\mathbf{X}_t - c))} \quad \rho > 0, \tag{8}$$

where ρ is the smoothing parameter, and c the transition parameter, both to be estimated. This function allows the parameters to change monotonically with $\mathbf{e}_i'\mathbf{X}_t$. As $\rho \to \infty$, $F(\mathbf{e}_i'\mathbf{X}_t)$ becomes a Heaviside function:

$$F(\mathbf{e}_i'\mathbf{X}_t) = \begin{cases} 1 & \text{if} \quad \mathbf{e}_i'\mathbf{X}_t > c \\ 0 & \text{if} \quad \mathbf{e}_i'\mathbf{X}_t \leq c \end{cases}$$

and (8) reduces to the TAR model in (6). As $\rho \to 0$, (7)-(8) becomes a linear model because regime switching becomes impossible.

Second, the exponential function allows differing behaviour depending on the size of the transition variable, or distance from the transition value, with the resulting model referred to as the Exponential STR (or ESTR) model:

$$F(\mathbf{e}_i'\mathbf{X}_t) = 1 - \exp(-\rho(\mathbf{e}_i'\mathbf{X}_t - c)^2) \quad \rho > 0 \tag{9}$$

where the parameters in (9) change symmetrically about c with $\mathbf{e}_i'\mathbf{X}_t$. If $\rho \to \infty$ or $\rho \to 0$ the ESTR model becomes linear, while non-linearities require intermediate values for ρ. This model implies that the dynamics obtained for values of the transition variable close to c differ from those obtained for values that largely differ from c. This represents a generalisation of the regular exponential autoregressive (EAR) model of Haggan and Ozaki (1981), where $\theta_0 = c = 0$, this generalisation making the EAR model location invariant.

A particular issue in estimating smooth transition models concerns the smoothing parameter, ρ, estimation of which has in practice been problematic. In the LSTR model, a large ρ results in a steep slope of the transition function at c, thus a large number of observations in the neighbourhood of c are required to estimate ρ accurately. Additionally, a result of this is that convergence of ρ may be slow, with relatively large changes in ρ having only a minor effect upon the shape of the transition function. A solution to this problem, suggested by Teräsvirta and Anderson (1992), Granger and Teräsvirta (1993) and Teräsvirta (1994) is to scale the smoothing parameter, ρ, by the standard deviation of the transition variable, and similarly in the ESTR model to scale by the variance of the transition variable. Thus, the LSTR and ESTR models become respectively:

$$
\begin{aligned}
F(\mathbf{e}_i'\mathbf{X}_t) &= \frac{1}{1+\exp\left(-\rho\frac{\mathbf{e}_i'\mathbf{X}_t-c}{\sigma(\mathbf{e}_i'\mathbf{X}_t)}\right)} \\
F(\mathbf{e}_i'\mathbf{X}_t) &= 1-\exp\left(-\rho\frac{(\mathbf{e}_i'\mathbf{X}_t-c)^2}{\sigma^2(\mathbf{e}_i'\mathbf{X}_t)}\right),
\end{aligned}
$$

where $\sigma^2(\mathbf{e}_i'\mathbf{X}_t)$ is the variance of the i-th predictor. When applying these non-linear models, a key decision is the choice of the transition variable. For both the TAR and STR model we follow the same basic procedure. It should be noted that for the STR models a selection procedure for choosing between LSTR and ESTR models has been set out by Teräsvirta and Anderson (1992) and Granger and Teräsvirta (1993). However, we wish to systematically estimate both version of the models and so our procedure is a slight variation of their procedure but follows the same spirit. Over the in-sample period we estimate each of the TAR, LSTR and ESTR models in turn with a different transition variable and select the variable that produces the smallest sum of squared residuals. This is equivalent to set (for instance)

$$
\hat{\imath}^j \equiv \arg\min_{\{1,2,\ldots,m\}} \sum_{t=1}^{T} \left\{ r^j_{t+h} - \alpha^j_{h,1} - (\beta^j_{h,1})'\mathbf{X}_t - [\alpha^j_{h,2} + (\beta^j_{h,2})'\mathbf{X}_t] F(\mathbf{e}_i'\mathbf{X}_t) \right\}^2,
$$

where the choice of i may clearly depend on the specific series of stock/bond returns under investigation. The definition of $\hat{\imath}^j$ is similar for TAR models. A further complication arises because in TAR models the transition value c also needs to be "chosen".[6] In order to select the transition value for TAR models, we follow the general procedure in Chan (1993) where possible transition values (defined as the middle 70% of the ordered series) are selected with the models in equations (6) and (7) estimated and the appropriate transition value chosen as the one that minimises the sum of squared residuals, for instance

$$
\hat{c}^j_{\hat{\imath}^j} \equiv \arg\min_{c_{\hat{\imath}^j}\in C_{\hat{\imath}^j}} \sum_{t=1}^{T} \left\{ r^j_{t+h} - \alpha^j_{h,1} - (\beta^j_{h,1})'\mathbf{X}_t - [\alpha^j_{h,2} + (\beta^j_{h,2})'\mathbf{X}_t] F(\mathbf{e}_{\hat{\imath}^j}'\mathbf{X}_t) \right\}^2,
$$

where $C_{\hat{\imath}^j}$ is the set that contains the middle 70% of the empirical distribution of the selected (SSR-minimizing) transition variable $\mathbf{e}_{\hat{\imath}^j}'\mathbf{X}_t$.

In addition to the above procedures we also consider a further transition variable for each of the models in this sub-section. Here we allow a forecaster to use a prediction of the dependent variable as the transition variable rather than just using one (or a combination of) the observable variables. In particular, we estimate a linear version of the predictive regression model (i.e., (1)) and obtain the fitted values for the dependent variable, which in turn is used as the transition variable in the TAR and STR models. Finally, we also estimate a LSTR-GARCH model and allow the fitted GARCH(1,1) variance to act as the transition

[6] For STR models the transition value c is estimated jointly with the regression coefficients in equation (7).

variable:

$$
\begin{aligned}
r^j_{t+h} &= \alpha^j_{h,1} + (\beta^j_{h,1})'\mathbf{X}_t + [\alpha^j_{h,2} + (\beta^j_{h,2})'\mathbf{X}_t]F(\mathbf{e}_i'\mathbf{X}_t) + \epsilon^j_{t+h} \\
h^j_{t+1} &= \omega^j + \zeta^j(\eta^j_t)^2 + \theta^j h^j_t \\
F(\mathbf{e}_i'\mathbf{X}_t) &= \frac{1}{1+\exp\left(-\rho\frac{h^j_t - c}{\sigma(h^j_t)}\right)}
\end{aligned}
\tag{10}
$$

in which ϵ^j_t is assumed to be conditionally normal, and $\epsilon^j_t|\mathcal{I}_t \sim N(0, h^j_t)$, so that η^j_t is standard normal. In (10) 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. As a final point, in all models the delay parameter in the transition function is set to be equal to one, whilst in principle the choice of delay lag is an empirical one it is recommended that the delay lag is no greater than the lag length of the explanatory variables, which is chosen to be one.

4.5. *Other Standard Benchmarks*

Finally, we supplement the set of models employed in this paper with a number of standard benchmarks commonly employed in the both the empirical finance and the forecasting literature (see e.g., Stock and Watson, 2003). These are a simple a random walk with drift model,

$$r^j_{t+h} = \alpha^j + \epsilon^j_{t+h}, \tag{11}$$

in which the predicted asset return is simply the sample mean return computed at time t, $E_t[r^j_{t+h}] = \alpha^j$. In terms of financial theory, notice that (11) corresponds not to the absence of change in asset prices, but to existence of a constant factor of change in log-prices, i.e.,

$$r^j_{t+h} = \ln P^j_{t+h} - \ln P^j_{t+h-1} = \alpha^j + \epsilon^j_{t+h}$$

implies

$$\ln P^j_{t+h} = \alpha^j + \ln P^j_{t+h-1} + \epsilon^j_{t+h}.$$

Obviously, even if only a crude description of the stochastic process for log-asset prices, (11) may represent an excellent forecasting model because the presence of only one parameter to be estimated (α^j) has a chance to reduce the amount of parameter uncertainty affecting the predictions.

A second, related benchmark is a simple autoregressive framework by which

$$r^j_{t+h} = \alpha^j + \beta^j r^j_t + \epsilon^j_{t+h}. \tag{12}$$

Clearly, (12) corresponds to a typical AR(1) model only when $h = 1$, while its structure is a bit more a-typical for $h > 1$. To increase the set of useful benchmarks to be used to compute relative forecasting performances, (11) and (12) are also estimated incorporating simple (Gaussian) GARCH(1,1)-in mean effects:

$$r^j_{t+h} = \alpha^j + \gamma\hat{\sigma}^j_{t+h} + \epsilon^j_{t+h}$$

and

$$r^j_{t+h} = \alpha^j + \beta^j r^j_t + \gamma\hat{\sigma}^j_{t+h} + \epsilon^j_{t+h}$$

where $\epsilon^j_t|\mathcal{I}_t \sim N(0, h^j_t)$. These benchmarks are important to quantify the pure forecasting performance of ARCH-in mean effects stripped out of the predictive power of the macroeconomic variables that enter $\mathbf{X}_t$.

5. **Evalution Methodologies: Testing for Superior Predictive Accuracy**

Given our objective of finding when and where non-linear models and/or models that allow the variance from predictive regression to affect – either directly (through appearance in a predictive regression) or indirectly (through the definition of regime switching dynamics, in non-linear models) – the forecasting performance, may be useful in practice to predict stock and bond returns, in this paper we resort to an wide array of alternative performance measures and procedures for testing the null of equal predictive accuracy across pairs of models. In this section, we briefly describe such measures and testing methodologies, providing relevant references and commenting on their advantages and disadvantages in the light of the stated goals of our research.

Define the time t forecast error from model μ, horizon h, and asset j (equal to either stocks or bonds) as:

$$e^{j,\mu}_{t,t+h} = r^j_{t+h} - \hat{r}^{j,\mu}_{t,t+h}, \tag{13}$$

where $\hat{r}^{j,\mu}_{t,t+h}$ comes from any of the twenty alternative models – both linear and non-linear – defined in Section 4. Therefore, for each combination defined by market (type of asset returns forecasted), model and horizon, we proceed to compute and report six difference measures of prediction accuracy (generally referred to as "performance"):

1. **Root Mean Squared Forecast Errors (MSFE).** The root mean squared forecast error is computed as

$$RMSFE^{j,\mu}_h = \sqrt{\frac{1}{T-h}\sum_{t=1}^{T-h}(e^{j,\mu}_{t,t+h})^2}, \tag{14}$$

   where T is the total sample size available. As it well know, taking the square root of the MSFE makes this index of predictive performance comparable to the original data in terms of unit of measurement.

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

$$Bias^{j,\mu}_h = \frac{1}{T-h}\sum_{t=1}^{T} e^{j,\mu}_{t,t+h}. \tag{15}$$

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

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

$$\begin{aligned} FEV_h^{j,\mu} &= \frac{1}{T-h}\sum_{t=1}^{T-h}(e_{t,t+h}^{j,\mu})^2 - \left[\frac{1}{T-h}\sum_{t=1}^{T} e_{t,t+h}^{j,\mu}\right]^2 \\ &= \frac{1}{T-h}\sum_{t=1}^{T-h}(e_{t,t+h}^{j,\mu})^2 - [Bias_h^{j,\mu}]^2, \end{aligned} \tag{16}$$

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:

$$MAFE_h^{j,\mu} = \frac{1}{T-h}\sum_{t=1}^{T}\left|e_{t,t+h}^{j,\mu}\right|. \tag{17}$$

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 value:

$$MPFE_h^{j,\mu} = \frac{1}{T-h}\sum_{t=1}^{T}\frac{e_{t,t+h}^{j,\mu}}{r_{t+h}^{j}}. \tag{18}$$

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:

$$SR_h^{j,\mu} = \frac{1}{T-h}\sum_{t=1}^{T} I_{\{r_{t+h}^{j}\hat{r}_{t,t+h}^{j,\mu}>0\}}, \tag{19}$$

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 argued in a number of papers in empirical finance for many trading strategies it is actually more important that a forecast function may deliver predictions with a correct sign than predictions which are quantitatively very accurate (i.e., it is 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 for relatively small asset returns).

Naturally, a simple ranking of forecasting models based on any of these six measures cannot be completely compelling: the fact that model μ_1 proves more accurate than model μ_2 does not imply that – in inferential terms – the null hypothesis that the difference between μ_1 and μ_2 is statistically significant.

We therefore employ four different methodologies to test whether any differences may be supported in statistical terms. The first and simplest among these testing methodologies has been introduced by Mincer and Zarnowitz (1969) and takes the form of a simple regression:

$$r^{j}_{t+h} = \varphi^{j}_{h,0} + \varphi^{j}_{h,1}\hat{r}^{j,\mu}_{t,t+h} + \xi^{j,\mu}_{t,t+h}, \tag{20}$$

where $\xi^{j,\mu}_{t,t+h}$ is a martingale difference sequence with constant variance σ^2_{ξ}. A good (sometimes said unbiased and efficient) forecast model implies that $\varphi^{j}_{h,0} = 0$ and $\varphi^{j}_{h,1} = 1$ so that

$$r^{j}_{t+h} = \hat{r}^{j,\mu}_{t,t+h} + \xi^{j,\mu}_{t,t+h} \Longleftrightarrow r^{j}_{t+h} - \hat{r}^{j,\mu}_{t,t+h} = e^{j,\mu}_{t,t+h} = \xi^{j,\mu}_{t,t+h}$$

(this means that forecast errors are MDSs, i.e. they have no structure) and that 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). In what follows we present: (i) the R^2 from regression (20); (ii) the p-values of standard t-test of the separate null hypothesis that $\varphi^{j}_{h,0} = 0$ and $\varphi^{j}_{h,1} = 1$; (iii) the p-value from an F-test of the composite hypothesis that *simultaneously* $\varphi^{j}_{h,0} = 0$ and $\varphi^{j}_{h,1} = 1$.

Mincer and Zarnowitz's (1969) test heavily relies on parametric assumptions concerning $\xi^{j,\mu}_{t,t+h}$ 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, it happens that market traders may use forecasts not really to place bets based on the leve of the forecast, but on their signs. Pesaran and Timmermann (1992) propose a non-parametric market-timing (PT) test to investigate whether or not a model has economic value in forecasting the "direction" of asset price movement. The PT statistics can be computed in the following manner. First, compute $\hat{P}^{j,\mu}_{h}$, an estimate of the probability that r^{j}_{t+h} and its forecast $\hat{r}^{j,\mu}_{t,t+h}$ have the same sign "conditional" on independence of r^{j}_{t+h} from its forecast:

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

where

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

The PT statistics is then computed using

$$PT^{j,\mu}_{h} = \frac{SR^{j,\mu}_{h} - \hat{P}^{j,\mu}_{h}}{\sqrt{\widehat{Var}\left(SR^{j,\mu}_{h}\right) - \widehat{Var}\left(\hat{P}^{j,\mu}_{h}\right)}} \overset{a}{\sim} N(0,1), \tag{21}$$

where $SR^{j,\mu}_{h}$ is the success ratio for model μ at horizon h. As stressed in (21), Pesaran and Timmermann (1992) found that the asymptotic distribution of $PT^{j,\mu}_{h}$ is asymptotically normal. Using the asymptotic distribution, the PT statistic tests the null hypothesis that

H_o: r^{j}_{t+h} and $\hat{r}^{j,\mu}_{t,t+h}$ are independently distributed $\Longleftrightarrow$ model μ has no predictive power for the sign of r^{j}_{t+h}.

Notice that a necessary condition for the PT test to be implementable is that not all the observations of for r^{j}_{t+h} and its forecasts $\hat{r}^{j,\mu}_{t,t+h}$ have the same sign. If this condition is violated, the PT statistics is not defined because $\widehat{Var}\left(SR_h^{j,\mu}\right) = \widehat{Var}\left(\hat{P}_h^{j,\mu}\right)$ when all the observations for r_{t+h}^j and its forecasts $\hat{r}_{t,t+h}^{j,\mu}$ have the same sign.

Another test by now classical in the forecasting literature is Diebold and Mariano's (1995) equal predictive accuracy test. Importantly, this test draws the attention on the opportunity of testing whether the mean loss function values derived from two alternative forecasts μ_1 and μ_2 are different with high degree of statistical confidence. To derive the Diebold and Mariano (DM) statistics, first compute the differences of square loss functions of two competing models:

$$diff_{t,j,h}^{\mu_1,\mu_2} = L\left(e_{t,t+h}^{j,\mu_1}\right) - L\left(e_{t,t+h}^{j,\mu_2}\right). \tag{22}$$

The DM statistics is defined as

$$DM_{j,h}^{\mu_1,\mu_2} = \frac{\frac{1}{T-h}\sum_{t=1}^{T} diff_{t,j,h}^{\mu_1,\mu_2}}{\widehat{\sigma}\left(diff_{t,j,h}^{\mu_1,\mu_2}\right)} \tag{23}$$

As in Guidolin and Timmermann (2007) to compute an estimate of the standard error of the loss differential by using the standard Newey-West estimator

$$\widehat{\sigma}\left(diff_{t,j,h}^{\mu_1,\mu_2}\right) = \sqrt{\sum_{i=-h}^{h} \widehat{Cov}(diff_{t,j,h}^{\mu_1,\mu_2}, diff_{t+i,j,h}^{\mu_1,\mu_2})}.$$

Note that the square of the estimate can be negative. When this rare event arises, as Diebold and Mariano (1995) suggest, we treat $\widehat{\sigma}\left(diff_{t,j,h}^{\mu_1,\mu_2}\right)$ to be zero and automatically reject the null hypothesis. Diebold and Mariano (1995).also show that the DM statistics has an asymptotically normal distribution:

$$DM_{j,h}^{\mu_1,\mu_2} \overset{a}{\sim} N(0,1).$$

Using the asymptotic normal distribution, the following one-side hypothesis test can be implemented:

$$H_o: \quad E\left[diff_{t,j,h}^{\mu_1,\mu_2}\right] \leq 0 \Longleftrightarrow \text{model } \mu_1 \text{ outperforms model } \mu_2.$$

Of course, the same test procedure may be used to test the null that $E\left[diff_{t,j,h}^{\mu_1,\mu_2}\right] \geq 0$, i.e., that model μ_1 underperforms model μ_2. In this paper we implement DM test assuming a square loss function, i.e.

$$diff_{t,j,h}^{\mu_1,\mu_2} = \left(e_{t,t+h}^{j,\mu_1}\right)^2 - \left(e_{t,t+h}^{j,\mu_2}\right)^2.$$

Giacomini and White (2006, henceforth GW) have recently argued that standard out-sample predictive ability tests are not necessarily appropriate for real-time forecast methods. For instance, both $e_{t,t+h}^{j,\mu_1}$ and $e_{t,t+h}^{j,\mu_2}$ are usually generated from parametric models that have to be recursively estimated over time, i.e. $e_{t,t+h}^{j,\mu_1}$ and $e_{t,t+h}^{j,\mu_2}$ have to be themselves estimated using $\hat{e}_{t,t+h}^{j,\mu_1}$ and $\hat{e}_{t,t+h}^{j,\mu_2}$. This means that $\widehat{diff}_{t,j,h}^{\mu_1,\mu_2} = \left(\hat{e}_{t,t+h}^{j,\mu_1}\right)^2 - \left(\hat{e}_{t,t+h}^{j,\mu_2}\right)^2$ will be probably polluted by errors caused by estimation uncertainty concerning the parameters of the underlying models.[7] From a methodological point of view, GW shift the focus from the

[7] The theory in Diebold and Mariano (1995) was developed for the baseline case of no parameter uncertainty. Exceptions exist: for instance, the random walk model does not require estimation of any parameters.

unconditional mean of differences in loss functions (as in (23)) across prediction models to the conditional expectation of such differences across forecast methods, i.e. from the null

$$H_o : E\left[diff^{\mu_1,\mu_2}_{t,j,h}\right] = 0$$

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

$$H_o' : E_{t-1}\left[diff^{\mu_1,\mu_2}_{t,j,h}\right] = 0$$

under the estimated parameters of models μ_1 and μ_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.[8]

In the case $h = 1$ Giacomini and White (2006) exploit the fact that the null is equivalent to stating that $\{diff^{\mu_1,\mu_2}_{t,j,h}\}$ is a martingale difference sequence, implying that for all measurable functions g_t in the information set at time t it should be $E\left[g_t \cdot diff^{\mu_1,\mu_2}_{t,j,h}\right] = 0$.[9] 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 μ_1, μ_2 can be tested using the statistic

$$GW^{\mu_1,\mu_2}_{\mathbf{g}}(j,h) \equiv (T-h)\left[\frac{1}{T-h}\sum_{t=1}^{T}\mathbf{Z}^{\mu_1,\mu_2}_t(j,h)\right]'\left[\hat{\mathbf{\Omega}}(Z^{\mu_1,\mu_2}_t(j,h))\right]^{-1}\left[\frac{1}{T-h}\sum_{t=1}^{T}\mathbf{Z}^{\mu_1,\mu_2}_t(j,h)\right] \qquad (24)$$

where

$$\mathbf{Z}^{\mu_1,\mu_2}_t(j,h) \equiv \mathbf{g}_t \cdot diff^{\mu_1,\mu_2}_{t,j,h} \qquad \hat{\mathbf{\Omega}}(Z^{\mu_1,\mu_2}_t(j,h)) \equiv \sum_{i=-h}^{h}\widehat{Cov}\left[\mathbf{Z}^{\mu_1,\mu_2}_t(j,h), \mathbf{Z}^{\mu_1,\mu_2}_{t+i}(j,h)\right]$$

Under regularity conditions, $GW^{(m,n)}_{\mathbf{g}}(j,h) \overset{a}{\sim} \chi^2_{(q)}$. 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 $\mathbf{g}_t \equiv [1\ \Delta diff^{\mu_1,\mu_2}_{t,j,h}]'$ $(q = 2)$.[10]

6. **Empirical Results**

Presenting and commenting results for such an extensive experiment such as ours faces one obvious challenge: with 20 alternative econometric frameworks to be compared, 7 countries each yielding series of stock and bond return data, and 6 alternative performance measures, it is almost impossible to provide a detailed account for all the results obtained. In fact, when one considers that in this paper we have

[8] 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 $T \to \infty$.

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

[10] We also compute CPA tests when $\mathbf{g}_t \equiv [1\ \Delta dif^{(m,n,h)}_t\ \Delta dif^{(m,n,h)}_{t-1}\ e^{(m,h)}_t\ e^{(m,h)}_{t-1}\ e^{(n,h)}_t\ e^{(n,h)}_{t-1}]'$, i.e. $q = 7$. Results are qualitatively similar (in general, more favorable to non-linear models, in particular MSH models in which the Markov switching dynamics also involves the variance) and therefore omitted.

computed forecasts for three alternative horizons – $h = 1$, 3, and 12 months – a simple calculations reveals that we have obtained a minimum of 5,040 values for predictive accuracy measures of different types. Even when it comes to compare – for each given country and asset-type, and after selecting a forecast horizon – the relative forecasting performance to test for equal predictive accuracy, it easy to determine that with 20 models, tests can be performed for as many as 190 comparisons. This means that in total as many as 7,980 comparisons may be performed. Therefore in this Section we proceed by successive refinements. In section 6.1 we briefly describe our recursive forecasting experiment. In section 6.2 we summarize the main results by focussing our attention only on the "winners", i.e. – per each country/market and asset-type – the 3-4 models that consistently produce the best forecasts. In section 6.3 we comment results country by country and make our best effort to bring out in the open the most important empirical results delivered by our analysis.

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

We consider the following pseudo out-of-sample experiment. We recursively estimate all the 20 models 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 relatively 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.[11] 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.

6.2. *An Overview of Forecasting Performances*

Table 2 finds a synthetic way to present the bulk of our results: for each country and each of the six performance measures described in section 5, we simply report the three best performing models found in our pseudo-out of sample forecasting exercise. The first panel of Table 2 is to be compared to the remaining panels and shows a striking result: although exceptions exist, in the case of the U.S. and the U.K. the contribution of non-linear models to a good predictive performance is massive. Especially in the case of stock returns and for short forecasting horizons, the two Markov switching models entertained in this paper show a robust ability to minimize the RMSFE, the MAFE, as well as the MPFE. This confirms the results on the considerable accuracy of MS models in Guidolin and Ono (2006, for the U.S.) and Guidolin and Timmermann (2005, for the U.K.). The excellent RMSFE performance derives from the fact that Markov switching (MS) models produce a very low forecast error variance, generally among the top three performers. However, MS models are generally not the models yielding the least possible average bias; in

[11] To save space, in what follow we systematically report results for $h = 1$ and 12 months and use text comments and/or footnotes to make a few remarks about performances in the case $h = 3$ months.

fact, especially at 12-month forecast horizons, other non-linear prediction frameworks (such as the ESTAR) and ARCH-in mean models seem to reduce the average bias. Interestingly, there is no clear ranking across MS and MSH models, although the former tends to outperform the latter in a majority of cases; however it remains difficult to propose a simple "count"- or "eye-ball"-based test of the implicit ranking between MS and MSH. Again the first panel of Table 2 shows that the evidence is slightly more mixed when it comes to forecasting bond returns. In general MS and MSH models still tend to systematically appear among the three best performing models, but in an increasing percentage of cases (as defined by each measures for the U.S. and the U.K., respectively) also TAR and STAR models offer a good predictive performance, along with the simple benchmarks.

Looking at the second and third panels of Table 2 allows us to oppose to the top performance of Markov switching models in predicting U.S. and U.K. stock and bond returns to rather different results obtained for the remaining five of the G7 countries. In the case of Japanese stock returns, the performance of the LSTAR model when the transition variable is the short-term T-bill rate change is generally very strong and robust. In the Japanese case, MS and MSH remain rather accurate models, but only in a few metrics (such as the average bias and MPFE). However, the fact the Markov switching models yield now rather large forecast error variances, prevents them to produce leading performances in the standard RMSFE metric and, for similar reasons, also in the MAFE metric. Results for German stock returns are very hard to summarize in any useful way. The impression is that with six criteria and three podium spots available (for a total of 18 winning models that can be reported in the table), at least a dozen model make it to show some kind of "top" level performance. However some weak indications may anyway be extracted: the LSTAR GARCH model (in which GARCH variance acts as the transition variable) seems to work well for a number of criteria, although it must also be noticed that ARCH-in mean models (of heterogeneous types) are in fact excellent in minimizing the MAFE for h = 1. Results are much easier to describe in the case of bond returns, for both Japan and Germany. In this case, there is an amazing consistency across different measures in terms of the best performing models, which are generally represented by simple benchmarks, such as the random walk (although in many cases the presence of a GARCH-in mean effect appears to improve performance); in the case of Germany, a simple homoskedastic AR(1) offers good performance. Non-linear models (especially of the TAR and STAR type) are only useful to minimize MPFE and the bias; in the case of German bond returns, the ESTAR model that uses changes in short-term rates as the transition variable turns out to be among the best models in many cases.

The third panel of Table 2 strengthens the impression that the forecasting performance is strictly dependent on the country and the asset market under investigation and that the finding the MS models offer a top performance in the case of the U.S. and the U.K. is an interesting results that cannot be easily generalized. The panel that refers to France, Canada, and Italy reveals that in three cases the need of non-linear frameworks in forecasting applications is rather weak. In the case of French bond returns, there is weak evidence of non-linear behavior; simple benchmarks (with a most a need to incorporate ARCH-in mean effects) dominate in terms of RMSFE, variance, MAFE, etc., while ARCH-type models seem to be good in terms of minimizing bias and MPFE. Also for Italian stock returns, simple benchmarks generally provide top performances (sometimes with a need for ARCH-in mean effects), although based on RMSFE minimization, it is LSTAR models that seem to be required. Moreover nonlinear models are definitely needed at all horizons to minimize the MPFE. In fact, similar remarks apply to Italian bond returns, where the benchmarks or ARCH-in models perform best over short horizon, but LSTAR models are best over long forecast horizons. In the case of French stock returns, simple (like AR) models minimize bias while highly nonlinear models (such as ESTARs and LSTARs) minimize RMSFE, forecast error variance, MAFE, and SR. Over long horizons, t-Student ARCH models tend to also perform relatively well. In other countries and markets the evidence in favor of non-linear modeling is instead powerful. In the case of Canadian stock and bond returns, one seems to need strong non-linearities, although at times also simple benchmarks (especially when incorporating ARCH-in effects) give occasional top performance. Similarly, in the case of bond returns the non-linear effects revealed by the performance rankings are strong at h = 12, while at h = 1 simple random walk models corrected by ARCH-in mean effects provide good forecasts. In particular, the evidence in favor of LSTAR is important, especially when the objective is minimize MAFE.

6.3. *Country and Asset Specific Results*

Table 3 give detailed results on predictive performance for each country and for stock and bond returns, separately in different of the table. Table 4 gives the results of DM and GW tests for stock returns. In the case of U.S., U.K., and Japan we report in detail test results for both h = 1 and h = 12, while for the remaining G7 countries we save space by only presenting results for the h = 1 case. Finally, Table 5 presents the results of DM and GW tests for bond returns. In this case, we save space by reporting results only for the h = 1 case.

In Table 4, we have evidence from the DM test that for the U.S. and h = 1 all models are significantly less accurate than MS and MSH which dominate in the prediction of stock returns. The only exception is TAR-SRF which seems to be rather robust and cannot be told apart from MS and MSH in statistical terms. These findings also apply under GW tests, although in some cases the p-values fall between 5 and 10Interestingly, while DM tests cannot distinguish the performance of MS vs. MSH on statistical grounds, under GW tests MS appears slightly better than MSH: apparently having the Markov state influenced by a regime-switching variance does not improve prediction accuracy. Unreported results confirm that these findings hold also for h = 3. In the case of h = 12, while DM tests keep showing that MS and MSH are statistically superior to all other frameworks employed in this paper, GW tests stop giving strong signals. Again for the U.S., Table 5 reveals that both DM and GW tests give results generally consistent with those obtained for the prediction of stock returns. However the evidence provided by the DM test weakens considerably in the case of h = 12. No evidence whatsoever may be derived from GW tests in this case. When applied to U.K. results, Tables 4 and 5 give results which are qualitatively similar to those commented for the U.S. In this case however, GW results are slightly weaker (e.g., we find no evidence of a statistically significant difference between MS and MSH models and the LSTAR in which the switching variables is the change in T-bill rates). However, differently from the U.S., equal predictive accuracy tests give increasingly stronger results as h increases. For instance, for h = 3 there is weak (p-value is 0.09) GW evidence that MS and MSH may differ (and this presumably means that MS is more accurate than MSH). Results are similar for bond returns, even though in this case DM evidence is considerably weaker in the case of h = 12. In this case GW tests are completely inconclusive.

Results are structurally different in the case of the remaining five G7 countries: for these combinations of countries and markets, in most cases both DM and GW tests are inconclusive. For Japanese stock and bond returns, p-values are large and reveal weak statistical differences for most horizons and pairs of models. There is only some evidence that for h = 12 the LSTAR model that uses changes in T-bill rates as a switching variable may statistically outperform roughly half among the weakest competing models. In the case of Germany, as the tables show (significant p-values are boldfaced), there is only some evidence of under-performance of EGARCH models at h = 12 and of out-performance of LSTAR-GARCH models vs. a few other models.

7. **Conclusion**

In this paper we have systematically examined the comparative predictive performance of a number of alternative non-linear models for stock and bond returns in the G7 countries. Among the non-linear frameworks employed, we also estimate univariate models in which conditional heteroskedasticity is captured through standard GARCH and EGARCH models and ARCH-in mean effects appear in the conditional mean equation. As one may have expected, we fail to find a consistent winner/out-performer across all countries and asset markets: the general finding is that depending on the forecast horizon, the country, and the market (stock or bond), the best performing model changes, sometimes abruptly. Although in most combinations of horizons, countries, and markets, it turns out that capturing non-linear effects - may it be through Markov switching, threshold, or smooth transition frameworks - is usually of extreme importance to improve the forecasting performance, cases can be found in which simple benchmarks - such as the random walk, or a simple AR(1) - may in fact deliver consistently accurate predictive performance. Two additional results emerge. First, U.S. and U.K. asset return data (and, to a lesser extend, Canadian) appear to be "special" in the sense that good predictive performance seems to loudly ask for modeling non-linear effects, especially of the Markov switching type. Although occasionally also stock and bond returns from other G7 countries appear to require non-linear modeling (especially of TAR and STAR type), data from France, Germany, and Italy may often express interesting predictive results on the basis of rather simple benchmarks, at times a naive linear homoskedastic model. Second, U.S. and U.K. data appear once more "special" because they are the only two countries in which the data are rich enough to allow us to test and find statistically significant difference between forecasting models.

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Data Appendix

Variable	Source	Mnemonic
Stock Return 100*[ln(p_t)-ln(p_{t-1})]	Total Market Index, Datastream	TOTMKCN(RI), TOTMKFR(RI), TOTMK TOTMKIT(RI), TOTMKJP(RI), TOTMKU TOTMKUS(RI)
Bond Return 100*[ln(p_t)-ln(p_{t-1})]	Total Bond Return Index, Global Financial Database	TRCANGVM, TRFRAGVM, TRDEUGVM, TRITAGVM, TRJPNGVM, TRGBRGVM, TRUSG10M
Dividend Yield $\ln\left(\frac{DY_t}{100}\right)$	Total Market Index, Datastream	TOTMKCN(DY), TOTMKFR(DY), TOTMKBD(DY), TOTMKIT(DY), TOTMKJP(DY), TOTMKUK(DY), TOTMKUS(DY)
Change in Short-term interest rate tb_t - tb_{t-1}	3 Month Treasury Bill (tb), Global Financial Database	ITCAN3D, ITFRA3D, ITDEU3D, ITITA3W, ITJPN3D, ITGBR3D, ITUSA3SD
Term Spread gb_t - tb_t	10 Year Government Bond (gb), Datastream	CNI61..., FRI61..., BDI61..., ITI61..., JPI61..., UKI61..., USI61...
Inflation 100*[ln(p_t)-ln(p_{t-1})]	Consumer Price Index, Datastream Seasonally adjusted using Stock and Watson (2003) procedure.	CNI64...F, FRI64...F, BDCONPRCE, ITI64...F, JPI64...F, UKI64...F, USI64...F
Industrial Production 100*[ln(p_t)-ln(p_{t-1})]	Industrial Production, Datastream Seasonally adjusted using Stock and Watson (2003) procedure.	CNI66..IG, FRI66..IG, BDI66..IG, ITI66..IG, JPI66..IG, UKI66..IG, USI66..IG
Exchange Rate 100*[ln(p_t)-ln(p_{t-1})]	Nominal Effective Trade Weighted Exchange Rate, Datastream	CNI..NEUE, FRI..NEUE, BDI..NEUE, ITI..NEUE, JPI..NEUE, UKI..NEUE, USI..NEUE
Change in Unemployment Rate un_t - un_{t-1}	Unemployment rate (seasonally adjusted), Global Financial Database	UNCANM, UNFRAM, UNDEUM, UNITAM, UNJPNM, UNGBRM, UNUSAM
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 for each of the G7 countries. 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
Canada					**Asset Returns**			
Stock return	1.0134	1.2299	4.4513	-0.9106	7.4529	324.03**	2.9114	13.812**
Bond return	0.8351	0.8759	2.6787	0.2653	7.3969	274.61**	5.9955	57.983**
					Prediction Variables			
Log dividend yield	-3.6300	-3.6250	0.3528	0.0244	2.4555	4.1846	1278.1**	1283.4**
Δ 3month T-bill yield	-0.0197	-0.0100	0.6133	0.3601	13.5841	1575.6**	32.618**	18.261**
Term spread	1.1774	1.4500	1.7938	-0.8257	3.2979	39.419**	995.99**	697.66**
CPI inflation rate	0.3097	0.2804	0.3329	0.3469	3.8153	16.046**	319.73**	453.46**
Industrial production growth	0.1713	0.1379	1.3806	0.3292	5.2442	76.578**	33.773**	19.289**
Δ log effective exchange rate	0.0015	0.0045	1.1665	0.1198	3.0130	0.8065	20.826**	29.473**
Δ unemployment rate	-0.0054	0.0000	0.3546	0.6957	6.2188	172.16**	1.7799	25.535**
France					**Asset Returns**			
Stock return	1.2124	2.0226	5.9220	-0.5618	4.7134	58.774**	3.8752	12.221*
Bond return	0.8225	1.0101	2.1119	-0.9124	8.2589	433.80**	24.057**	2.7837
					Prediction Variables			
Log dividend yield	-3.3953	-3.4389	0.3442	0.6962	3.1201	27.341**	1208**	1202.6**
Δ 3month T-bill yield	-0.0087	-0.0100	0.4616	1.5369	16.0851	2529.4**	28.258**	89.653**
Term spread	0.8646	1.0500	1.2366	-0.9456	4.1211	67.667**	961.60**	600.43**
CPI inflation rate	0.3180	0.2143	0.3378	1.1299	3.7328	79.017**	765.77**	873.29**
Industrial production growth	0.0530	0.0893	2.7120	-0.0950	3.8269	10.079**	203.58**	21.337**
Δ log effective exchange rate	-0.0249	-0.0347	0.8399	-0.7360	6.3714	189.46**	28.132**	12.858*
Δ unemployment rate	0.0098	0.0000	0.0990	-0.6148	14.5234	1880.2**	149.23**	8.3011
Germany					**Asset Returns**			
Stock return	0.7953	1.0168	5.2850	-0.9366	6.1028	183.91**	3.8094	11.501*
Bond return	0.5983	0.8569	1.7703	-0.5346	4.5715	50.583**	12.984*	41.351**
					Prediction Variables			
Log dividend yield	-3.8131	-3.8444	0.2961	0.4280	2.8213	10.708**	1190.6**	1189.7**
Δ 3month T-bill yield	-0.0011	0.0000	0.2858	0.2261	9.2164	543.88**	49.265**	20.786**
Term spread	1.3273	1.4900	0.8622	-0.2845	2.2453	12.508**	1073.3**	1016.3**
CPI inflation rate	0.1971	0.1376	0.2484	0.9522	5.7528	156.87**	66.759**	29.322**
Industrial production growth	0.1290	0.1656	1.4269	-0.1413	5.3489	78.360**	80.077**	57.528**
Δ log effective exchange rate	0.0953	-0.0271	0.9117	0.5517	3.6600	23.142**	34.518**	4.7180
Δ unemployment rate	0.0137	0.0000	0.1804	4.4505	70.2174	64363**	12.205*	0.4592
Italy					**Asset Returns**			
Stock return	1.2889	0.7745	6.9058	0.3016	4.3987	32.480**	9.2278	17.350**
Bond return	1.0430	1.0896	2.4986	-0.4891	10.2492	749.10**	52.398**	6.6148
					Prediction Variables			
Log dividend yield	-3.7382	-3.7235	0.3276	-0.2206	2.1337	13.232**	1084.9**	1078.8**
Δ 3month T-bill yield	-0.0211	-0.0204	0.6019	0.9074	8.0661	405.42**	3.1252	32.265**
Term spread	0.4777	0.6050	1.3436	-0.3632	2.4745	11.251**	904.79**	438.26**
CPI inflation rate	0.5011	0.3580	0.4228	1.2924	3.8248	103.07**	1014.8**	940.47**
Industrial production growth	0.1285	0.0035	2.6669	0.5201	5.2122	83.657**	82.829**	21.6414**
Δ log effective exchange rate	-0.1617	-0.0651	1.1513	-2.1336	20.4239	4505.2**	42.502**	44.653**
Δ unemployment rate	-0.0045	0.0000	0.2121	-8.8954	135.966	251949**	2.2023	0.1837

Table 1 [cont.]

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 for each of the G7 countries. 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
Japan					**Asset Returns**			
Stock return	0.5279	0.7439	5.3773	-0.3346	4.9126	57.484**	4.0889	24.870**
Bond return	0.4623	0.5563	2.2630	0.0838	6.9439	218.16**	10.973*	30.447**
					Prediction Variables			
Log dividend yield	-4.6986	-4.7105	0.3866	0.2559	2.4302	8.2120*	1245.4**	1248.0**
Δ 3month T-bill yield	-0.0087	0.0000	0.2258	0.1802	13.9259	1673**	13.665**	4.9545
Term spread	1.3275	1.3658	0.9288	0.1536	3.2129	1.9564	1032.4**	934.08**
CPI inflation rate	0.1091	0.0676	0.3055	1.0172	5.2313	127.64**	63.704**	53.242**
Industrial production growth	0.1647	0.1283	1.6197	0.0169	3.0172	0.0201	104.82**	10.214*
Δ log effective exchange rate	0.1626	-0.0794	2.4113	0.5068	4.0009	28.413**	35.099**	24.779**
Δ unemployment rate	0.0054	0.0000	0.1053	-0.1616	3.9435	13.925**	29.676**	24.215**
United Kingdom					**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 production growth	0.9869	1.4647	12.0630	-0.3860	4.1650	27.348**	16.913**	19.932**
Δ log effective 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**
United States					**Asset Returns**			
Stock return	1.0809	1.4679	4.1139	-0.8993	6.9741	266.41**	1.9893	5.4377
Bond return	0.7259	0.6874	2.7538	0.2822	5.1332	68.165**	8.8827	32.886**
					Prediction Variables			
Log dividend yield	-3.6326	-3.5899	0.5177	-0.0828	1.8103	20.199**	1313.4**	1319.6**
Δ 3month T-bill yield	-0.0128	0.0000	0.5419	-1.4663	16.5004	2672.1**	25.347**	80.013**
Term spread	1.7046	1.7600	1.3395	-0.3715	2.5108	11.081**	949.65**	837.16**
CPI inflation rate	0.3228	0.2750	0.2932	0.9466	4.7245	91.815**	355.95**	606.56**
Industrial production growth	0.2019	0.2263	0.6501	-0.4226	3.8477	20.062**	48.005**	15.413**
Δ log effective exchange rate	-0.0194	0.1683	1.7836	-0.2653	3.0245	3.9495	32.041**	1.6968
Δ unemployment rate	-0.0039	0.0000	0.1650	0.1855	4.4453	31.171**	39.737**	12.134*
Log dividend yield	0.3569	0.3415	8.4144	0.5537	7.1775	261.49**	22.871**	30.464**

Table 2

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

		United States		United Kingdom	
		Stocks	Bonds	Stocks	Bonds
RMSFE	h=1	1. MS 2. MSH 3. Gaussian-TGARCH(1,1)	1. MS 2. MSH 3. AR(1)	1. MS 2. MSH 3. Logistic STAR - T-bill	1. MS 2. MSH 3. Random walk with drift
	h=12	1. MS 2. MSH 3. Logistic STAR - SRL	1. MS 2. MSH 3. AR(1) with GARCH(1,1)-in mean	1. MS 2. MSH 3. Logistic STAR - T-bill	1. MS 2. MSH 3. Random walk w/GARCH(1,1)-in mean
Bias	h=1	1. Gaussian EGARCH(1,1)-in mean 2. MSH 3. Logistic STAR - T-bill	1. Logistic STAR-SRF 2. t-EGARCH(1,1)-in mean 3. Exponential STAR-SRF	1. Gaussian TGARCH(1,1)-in mean 2. t-Student TGARCH(1,1)-in mean 3. Gaussian GARCH(1,1)-in mean	1. MS 2. MSH 3. Gaussian GARCH(1,1)-in mean
	h=12	1. Exponential STAR - T-bill 2. Exponential STAR - SRL 3. Logistic STAR - SRL	1. TAR-SR 2. TAR-SRF 3. Gaussian-GARCH(1,1)	1. Linear homoskedastic 2. Gaussian GARCH(1,1)-in mean 3. MS	1. TAR-SRF 2. Logistic STAR - T-bill 3. MS
Forecast Variance	h=1	1. MS 2. MSH 3. Gaussian-TGARCH(1,1)	1. MSH 2. MS 3. AR(1)	1. MSH 2. MS 3. Logistic STAR - T-bill	1. MS 2. MSH 3. Random walk with drift
	h=12	1. MS 2. MSH 3. Random walk with drift	1. MSH 2. MS 3. AR(1)	1. MSH 2. MS 3. Logistic STAR - T-bill	1. MSH 2. MS 3. AR(1)
MAFE	h=1	1. MS 2. MSH 3. Gaussian-TGARCH(1,1)	1. MSH 2. MS 3. AR(1) with GARCH(1,1)-in mean	1. MS 2. MSH 3. t-GARCH(1,1)-in mean	1. MS 2. MSH 3. AR(1)
	h=12	1. MS 2. MSH 3. Random walk w/GARCH(1,1)-in mean	1. MSH 2. MS 3. AR(1) with GARCH(1,1)-in mean	1. MS 2. MSH 3. Random walk with drift	1. MS 2. MSH 3. Linear homoskedastic
MPFE	h=1	1. MS 2. MSH 3. AR(1) with GARCH(1,1)-in mean	1. TAR-SRF 2. Logistic STAR - T-bill 3. Gaussian-TGARCH(1,1)	1. MSH 2. MS 3. Gaussian EGARCH(1,1)-in mean	1. AR(1) w/GARCH(1,1)-in mean 2. MS 3. t-GARCH(1,1)-in mean
	h=12	1. MS 2. MSH 3. AR(1)	1. TAR-SRF 2. Logistic STAR-SRF 3. TAR-SR	1. t-Student TGARCH(1,1)-in mean 2. MS 3. Linear Homoskedastic	1. Exponential STAR - T-bill 2. TAR-SRF 3. Logistic STAR - T-bill
Success Ratio	h=1	1. MSH 2. MS 3. Gaussian-TGARCH(1,1)	1. MSH 2. MS 3. Random walk with drift	1. MSH 2. MS 3. Random walk with drift	1. MSH 2. MS 3. Random walk with drift
	h=12	1. MSH 2. MS 3. Random walk with drift	1. MSH 2. Random walk with drift 3. AR(1)	1. MS 2. MSH 3. Random walk with drift	1. Random walk with drift 2. MSH 3. MS

Table 2 [Cont.]

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

		Japan		Germany	
		Stocks	Bonds	Stocks	Bonds
RMSFE	h=1	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH(1,1)	1. Logistic STAR - T-bill	1. AR(1)
		2. AR(1)	2. AR(1) with GARCH(1,1)	2. Linear homoskedastic	2. AR(1) with GARCH(1,1)
		3. MSH	3. Random walk with drift	3. Exponential STAR - T-bill	3. Logistic STAR-GARCH(1,1)
	h=12	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH(1,1)	1. Logistic STAR-GARCH(1,1)	1. Logistic STAR-GARCH(1,1)
		2. Linear homoskedastic	2. AR(1)	2. Exponential STAR - T-bill	2. Logistic STAR - T-bill
		3. Gaussian TGARCH(1,1)-in mean	3. Random walk with drift	3. Logistic STAR - T-bill	3. AR(1)
Bias	h=1	1. MS	1. MS	1. AR(1)	1. TAR-SRF
		2. Gaussian EGARCH(1,1)-in mean	2. TAR-SR	2. Random walk with draft	2. Linear homoskedastic
		3. TAR-SRF	3. Logistic STAR-SRF	3. Linear homoskedastic	3. Logistic STAR-SRF
	h=12	1. Gaussian GARCH(1,1)-in mean	1. Gaussian TGARCH(1,1)-in mean	1. Random walk w/drift & GARCH(1,1)	1. TAR-SR
		2. Exponential STAR - T-bill	2. TAR-SR	2. AR(1) with GARCH(1,1)	2. Exponential STAR-SRF
		3. TAR-SRF	3. t-Student GARCH(1,1)-in mean	3. t-Student GARCH(1,1)-in mean	3. Logistic STAR-SRF
Forecast Variance	h=1	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH(1,1)	1. Logistic STAR - T-bill	1. AR(1)
		2. AR(1) w/GARCH(1,1)-in mean	2. AR(1) with GARCH(1,1)	2. t-Student GARCH(1,1)-in mean	2. AR(1) with GARCH(1,1)
		3. AR(1)	3. Random walk with drift	3. Linear homoskedastic	3. Logistic STAR-GARCH(1,1)
	h=12	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH(1,1)	1. Logistic STAR-GARCH(1,1)	1. Logistic STAR-GARCH(1,1)
		2. Linear homoskedastic	2. AR(1)	2. Exponential STAR - T-bill	2. Logistic STAR - T-bill
		3. Gaussian TGARCH(1,1)-in mean	3. Random walk with drift	3. Logistic STAR - T-bill	3. AR(1)
MAFE	h=1	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH(1,1)	1. Gaussian TGARCH(1,1)-in mean	1. Logistic STAR-GARCH(1,1)
		2. MSH	2. AR(1) with GARCH(1,1)	2. t-Student EGARCH(1,1)-in mean	2. AR(1)
		3. AR(1)	3. Random walk with drift	3. Gaussian GARCH(1,1)-in mean	3. AR(1) with GARCH(1,1)
	h=12	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH(1,1)	1. Exponential STAR - T-bill	1. Logistic STAR - T-bill
		2. Linear homoskedastic	2. AR(1)	2. TAR-SR	2. Logistic STAR-GARCH(1,1)
		3. TAR-SR	3. Random walk with drift	3. TAR-SRF	3. AR(1)
MPFE	h=1	1. MS	1. TAR-SR	1. Gaussian GARCH(1,1)-in mean	1. MS
		2. MSH	2. MS	2. TAR-SR	2. MSH
		3. TAR-SR	3. Exponential STAR - T-bill	3. TAR-SRF	3. TAR-SR
	h=12	1. TAR-SR	1. t-Student EGARCH(1,1)-in mean	1. Exponential STAR - T-bill	1. Logistic STAR - T-bill
		2. t-Student TGARCH(1,1)-in mean	2. TAR-SR	2. t-Student EGARCH(1,1)-in mean	2. MSH
		3. t-GARCH(1,1)-in mean	3. Exponential STAR - T-bill	3. MSH	3. TAR-SR
Success Ratio	h=1	1. TAR-SRF	1. Exponential STAR - T-bill	1. t-Student EGARCH(1,1)-in mean	1. Exponential STAR - T-bill
		2. Linear homoskedastic	2. Gaussian GARCH(1,1)-in mean	2. Random walk with draft	2. Logistic STAR-GARCH(1,1)
		3. Exponential STAR - T-bill	3. TAR-SR	3. Gaussian GARCH(1,1)-in mean	3. Linear homoskedastic
	h=12	1. Gaussian EGARCH(1,1)-in mean	1. TAR-SR	1. AR(1) with GARCH(1,1)	1. Logistic STAR - T-bill
		2. TAR-SR	2. Exponential STAR - T-bill	2. Random walk with draft	2. Exponential STAR - T-bill
		3. MS	3. Logistic STAR-GARCH(1,1)	3. MS	3. Logistic STAR-GARCH(1,1)

Table 2 [Cont.]

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

		France		Canada		Italy	
		Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
RMSFE	h=1	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH	1. Random walk with drift	1. AR(1)
		2. Exponential STAR - T-bill	2. AR(1) with GARCH(1,1)	2. t-Stud. EGARCH(1,1)-in mean	2. AR(1) with GARCH(1,1)	2. Random walk w/drift & GARCH	2. t-GARCH(1,1)-in mean
		3. Random walk with drift	3. Random walk with drift	3. AR(1)	3. Random walk with drift	3. AR(1) with GARCH(1,1)	3. t-Student TGARCH(1,1)-in mean
	h=12	1. Logistic STAR - T-bill	1. Linear homoskedastic	1. Logistic STAR - T-bill	1. Logistic STAR-SRF	1. AR(1)	1. Logistic STAR-GARCH(1,1)
		2. t-Student TGARCH(1,1)-in mean	2. AR(1)	2. Logistic STAR-SRF	2. Logistic STAR w/GARCH(1,1)	2. AR(1) with GARCH(1,1)	2. Logistic STAR-SRF
		3. t-Student GARCH(1,1)-in mean	3. Random walk with drift	3. Exponential STAR-SRF	3. AR(1) with GARCH(1,1)	3. Random walk with drift	3. Exponential STAR-SRF
Bias	h=1	1. Exponential STAR - T-bill	1. Gaussian GARCH(1,1)-in mean	1. Random walk w/drift & GARCH	1. Random walk w/drift & GARCH	1. Random walk w/drift & GARCH	1. t-Student EGARCH(1,1)-in mean
		2. TAR-SRF	2. t-Student GARCH(1,1)-in mean	2. AR(1)	2. AR(1) with GARCH(1,1)	2. AR(1) with GARCH(1,1)	2. Gaussian EGARCH(1,1)-in mean
		3. AR(1)	3. MS	3. Random walk with drift	3. Logistic STAR w/GARCH(1,1)	3. AR(1)	3. AR(1) with GARCH(1,1)
	h=12	1. AR(1) with GARCH(1,1)	1. Exponential STAR-SRF	1. Gaussian EGARCH(1,1)-in mean	1. Logistic STAR-SRF	1. Random walk w/drift & GARCH	1. t-Student EGARCH(1,1)-in mean
		2. Random walk with drift	2. TAR-SRF	2. Random walk with drift	2. Exponential STAR - T-bill	2. Linear homoskedastic	2. MSH
		3. AR(1)	3. Logistic STAR-GARCH(1,1)	3. AR(1) with GARCH(1,1)	3. Gaussian EGARCH(1,1)-in mean	3. AR(1) with GARCH(1,1)	3. MS
Forecast Variance	h=1	1. Logistic STAR - T-bill	1. Random walk w/drift & GARCH	1. Logistic STAR - T-bill	1. Random walk with drift	1. Logistic STAR - T-bill	1. Exponential STAR-SRF
		2. Exponential STAR - T-bill	2. AR(1) with GARCH(1,1)	2. t-Stud. EGARCH(1,1)-in mean	2. AR(1)	2. Random walk with drift	2. AR(1)
		3. Random walk with drift	3. Random walk with drift	3. Logistic STAR-SRF	3. Random walk w/drift & GARCH	3. Random walk w/drift & GARCH	3. Linear homoskedastic
	h=12	1. Logistic STAR - T-bill	1. AR(1)	1. Logistic STAR - T-bill	1. Logistic STAR-SRF	1. Logistic STAR - T-bill	1. Exponential STAR-SRF
		2. t-Student TGARCH(1,1)-in mean	2. Random walk with drift	2. Logistic STAR-SRF	2. Logistic STAR w/GARCH(1,1)	2. AR(1)	2. Logistic STAR-SRF
		3. t-Student GARCH(1,1)-in mean	3. Random walk w/drift & GARCH	3. Exponential STAR-SRF	3. AR(1) with GARCH(1,1)	3. AR(1) with GARCH(1,1)	3. Logistic STAR with GARCH(1,1)
MAFE	h=1	1. Exponential STAR - T-bill	1. AR(1) with GARCH(1,1)	1. AR(1)	1. Logistic STAR-SRF	1. Random walk with drift	1. AR(1)
		2. Logistic STAR - T-bill	2. AR(1)	2. Random walk with drift	2. Random walk with drift	2. Random walk w/drift & GARCH	2. Random walk w/drift & GARCH
		3. Exponential STAR-SRF	3. Random walk w/drift & GARCH	3. Random walk w/drift & GARCH	3. AR(1)	3. t-Student EGARCH(1,1)-in mean	3. t-GARCH(1,1)-in mean
	h=12	1. Exponential STAR-SRF	1. AR(1)	1. Logistic STAR - T-bill	1. Logistic STAR-SRF	1. AR(1) with GARCH(1,1)	1. Logistic STAR-GARCH(1,1)
		2. Logistic STAR - T-bill	2. Random walk with drift	2. Random walk w/drift & GARCH	2. Logistic STAR - T-bill	2. AR(1)	2. Logistic STAR-SRF
		3. Gaussian EGARCH(1,1)-in mean	3. Random walk w/drift & GARCH	3. Random walk with drift	3. Logistic STAR w/GARCH(1,1)	3. Random walk with drift	3. Exponential STAR-SRF
MPFE	h=1	1. Logistic STAR-SRF	1. t-Student EGARCH(1,1)-in mean	1. Exponential STAR - T-bill	1. Exponential STAR - T-bill	1. Logistic STAR-SRF	1. MS
		2. Gaussian EGARCH(1,1)-in mean	2. MS	2. TAR-SRF	2. Exponential STAR-SRF	2. Logistic STAR - T-bill	2. MSH
		3. t-Student GARCH(1,1)-in mean	3. Logistic STAR-SRF	3. TAR-SR	3. Random walk with drift	3. Exponential STAR - T-bill	3. Random walk w/drift & GARCH
	h=12	1. Exponential STAR - T-bill	1. Gaussian GARCH(1,1)-in mean	1. Linear homoskedastic	1. Exponential STAR - T-bill	1. Logistic STAR-SRF	1. t-Student GARCH(1,1)-in mean
		2. MSH	2. Exponential STAR-SRF	2. Gaussian GARCH(1,1)-in mean	2. Random walk w/drift & GARCH	2. Logistic STAR - T-bill	2. Linear homoskedastic
		3. t-Student GARCH(1,1)-in mean	3. Linear homoskedastic	3. Gaussian TGARCH(1,1)-in mean	3. Random walk with drift	3. Exponential STAR - T-bill	3. t-Student EGARCH(1,1)-in mean
Success Ratio	h=1	1. Logistic STAR - T-bill	1. Random walk with drift	1. AR(1)	1. Logistic STAR - T-bill	1. Random walk with drift	1. Random walk with drift
		2. Random walk with drift	2. AR(1)	2. Random walk with drift	2. Random walk with drift	2. Random walk w/drift & GARCH	2. Random walk w/drift & GARCH
		3. Random walk w/drift & GARCH	3. Random walk w/drift & GARCH	3. Random walk w/drift & GARCH	3. AR(1)	3. t-Student EGARCH(1,1)-in mean	3. t-Student EGARCH(1,1)-in mean
	h=12	1. Logistic STAR - T-bill	1. Linear homoskedastic	1. AR(1) with GARCH(1,1)	1. Logistic STAR - T-bill	1. AR(1) with GARCH(1,1)	1. Random walk with drift
		2. Gaussian EGARCH(1,1)-in mean	2. Random walk with drift	2. Random walk with drift	2. Logistic STAR w/GARCH(1,1)	2. Random walk with drift	2. AR(1)
		3. t-Student GARCH(1,1)-in mean	3. AR(1)	3. AR(1)	3. Random walk with drift	3. AR(1)	3. Random walk w/drift & GARCH

Table 3

Predictive Accuracy Measures for Stock and Bond Returns

Panel A: United States 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	4.219	4.540	0.100	-0.138	17.790	20.590	3.278	3.539	0.891	0.535	0.625	0.564	0.817	**-1.993**	0.004	0.060	0.162	0.000	0.088	0.000	0.223	0.000
Random walk (with drift)	4.195	4.342	-0.245	-0.435	17.534	**18.664**	3.234	3.365	0.343	0.333	0.660	**0.632**	N.A.	N.A.	0.000	0.006	**0.659**	0.268	**0.607**	**0.218**	**0.687**	0.241
AR(1)	4.202	4.386	-0.244	-0.419	17.598	19.062	3.230	3.409	0.296	**0.255**	0.660	0.632	N.A.	N.A.	0.001	0.033	0.406	0.013	0.340	0.005	0.499	0.011
Random walk (with drift and GARCH(1,1))	4.209	4.339	-0.192	-0.381	17.676	18.679	3.273	**3.361**	0.330	0.311	0.660	0.632	N.A.	N.A.	0.007	0.003	0.150	**0.366**	0.122	**0.283**	0.260	**0.337**
AR(1) with GARCH(1,1)	4.209	4.387	-0.185	-0.292	17.681	19.163	3.261	3.424	**0.268**	0.350	0.660	0.624	N.A.	-0.767	0.002	0.032	0.263	0.010	0.199	0.004	0.381	0.011
GARCH(1,1) in mean and exogenous predictors	4.253	4.543	0.269	-0.087	18.018	20.630	3.293	3.557	0.880	0.577	0.576	0.549	0.274	**-2.004**	0.007	**0.063**	0.069	0.000	0.023	0.000	0.057	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	4.287	4.517	-0.581	-0.255	18.041	20.342	3.240	3.515	0.698	0.441	0.625	0.586	-0.260	-1.473	0.007	0.044	0.392	0.001	0.022	0.000	0.020	0.000
EGARCH(1,1)-in mean and exogenous predictors	4.152	4.583	**-0.022**	-0.155	17.236	20.980	3.160	3.564	0.768	0.476	0.604	0.602	0.470	0.058	0.027	0.046	0.429	0.001	0.204	0.000	0.444	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	4.256	5.487	-0.496	0.645	17.871	29.688	3.246	4.405	0.721	1.274	0.604	0.481	-1.047	-1.609	0.009	0.002	0.436	0.032	0.042	0.000	0.047	0.000
TGARCH(1,1)-in mean and exogenous predictors	**4.136**	4.526	0.253	-0.125	**17.045**	20.467	**3.159**	3.505	0.577	0.649	**0.667**	0.586	**2.748**	-0.678	**0.040**	0.029	0.187	0.004	0.152	0.000	0.274	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	4.291	4.542	-0.600	-0.384	18.051	20.483	3.237	3.524	0.696	0.404	0.632	0.564	-0.279	**-2.374**	0.006	0.038	0.391	0.002	0.022	0.000	0.018	0.000
Exponential STAR - T-bill	4.401	4.452	0.188	**-0.025**	19.337	19.824	3.425	3.426	0.943	0.896	0.556	0.526	0.003	-0.570	0.000	0.009	0.023	0.163	0.000	0.002	0.001	0.007
Exponential STAR-SRF	4.219	4.330	0.100	**-0.063**	17.790	18.743	3.278	3.376	0.890	0.973	0.625	0.579	0.817	0.138	0.004	0.008	0.162	**0.369**	0.088	0.130	0.223	**0.311**
Logistic STAR - T-bill	4.253	4.370	**-0.056**	-0.214	18.085	19.054	3.296	3.407	0.791	0.838	0.611	0.571	0.083	-0.535	0.005	0.010	0.148	0.345	0.020	0.031	0.066	0.082
Logistic STAR-SRF	4.219	**4.329**	0.100	**-0.064**	17.790	18.739	3.278	3.375	0.891	0.973	0.625	0.579	0.817	0.138	0.004	0.008	0.162	**0.371**	0.088	**0.131**	0.223	**0.313**
TAR-SR	4.418	4.491	0.104	-0.158	19.506	20.146	3.462	3.483	1.076	1.191	0.535	0.511	-0.624	-0.845	0.001	0.006	0.027	0.165	0.000	0.001	0.000	0.003
TAR-SRF	6.960	7.628	0.380	0.612	48.299	57.807	3.907	4.154	0.988	1.122	0.590	0.556	-0.551	-0.716	0.009	0.000	0.005	0.034	0.000	0.000	0.000	0.000
Logistic STAR-GARCH(1,1)	4.304	4.432	-0.131	-0.225	18.510	19.591	3.337	3.466	0.733	0.723	0.583	0.579	-0.700	0.138	0.003	0.003	0.103	0.208	0.004	0.006	0.014	0.020
MS Two-state homoskedastic	**3.642**	**3.757**	-0.076	-0.139	**13.261**	**14.092**	**2.854**	**2.931**	**0.126**	**0.239**	**0.708**	**0.737**	**3.445**	**4.749**	**0.245**	**0.341**	**0.592**	0.002	**0.513**	0.000	**0.782**	0.000
MS Two-state heteroskedastic	**3.740**	**3.811**	**0.047**	0.190	**13.985**	**14.490**	**2.955**	**3.056**	**0.192**	**0.010**	**0.701**	**0.707**	**3.151**	**3.874**	**0.205**	**0.367**	**0.789**	0.015	**0.417**	0.000	**0.711**	0.000

Panel B: United States 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	2.156	2.039	0.106	0.049	4.638	4.156	1.655	1.575	-0.179	0.864	0.576	0.549	-0.062	-0.733	0.001	0.002	0.003	**0.079**	0.000	0.014	0.000	0.048
Random walk (with drift)	2.025	2.038	-0.238	-0.410	4.045	3.984	1.576	1.598	-0.328	-0.528	**0.653**	**0.632**	N.A.	N.A.	0.000	0.000	**0.953**	**0.712**	**0.896**	**0.622**	**0.369**	**0.059**
AR(1)	**2.022**	2.037	-0.208	-0.419	**4.044**	**3.972**	1.572	1.594	-0.288	-0.344	0.646	**0.632**	-0.732	N.A.	0.006	0.002	**0.689**	**0.871**	**0.356**	**0.918**	**0.307**	**0.058**
Random walk (with drift and GARCH(1,1))	2.027	2.021	-0.120	-0.274	4.096	4.008	1.576	1.597	-0.098	-0.502	0.653	0.632	N.A.	N.A.	**0.022**	0.000	0.032	**0.569**	0.026	**0.324**	**0.064**	**0.183**
AR(1) with GARCH(1,1)	2.026	**1.999**	-0.100	-0.278	4.095	3.919	**1.570**	**1.571**	-0.076	-0.297	0.639	0.632	-1.039	N.A.	0.002	**0.015**	**0.308**	**0.616**	**0.161**	**0.994**	**0.314**	**0.279**
GARCH(1,1) in mean and exogenous predictors	2.149	2.027	0.116	**-0.035**	4.606	4.107	1.650	1.586	-0.155	0.885	0.583	0.571	0.080	-0.394	0.002	0.006	0.002	**0.171**	0.000	0.026	0.000	**0.080**
GARCH(1,1)-in mean and exogenous predictors - t dist.	2.159	2.048	0.088	0.048	4.655	4.191	1.655	1.601	-0.202	1.139	0.583	0.556	0.080	-0.217	0.002	0.003	0.002	**0.072**	0.000	0.007	0.000	0.026
EGARCH(1,1)-in mean and exogenous predictors	2.159	2.041	-0.137	0.060	4.642	4.163	1.656	1.585	-0.437	0.826	0.604	0.564	0.148	-0.423	0.003	0.003	0.006	**0.076**	0.000	0.012	0.000	0.040
EGARCH(1,1)-in mean and exogenous predictors- t dist.	2.189	2.037	**0.009**	0.066	4.790	4.143	1.682	1.586	-0.471	0.985	0.597	0.564	0.374	-0.298	0.002	0.004	0.003	**0.083**	0.000	0.016	0.000	0.050
TGARCH(1,1)-in mean and exogenous predictors	2.165	2.044	0.040	-0.035	4.684	4.177	1.652	1.592	**0.029**	0.599	0.590	0.571	0.101	-0.394	0.006	0.002	0.001	0.107	0.000	0.010	0.000	0.035
TGARCH(1,1)-in mean and exogenous predictors- t dist.	2.173	2.062	0.053	0.069	4.717	4.247	1.667	1.599	-0.064	0.856	0.583	0.571	0.080	0.195	0.001	0.001	0.003	0.046	0.000	0.003	0.000	0.012
Exponential STAR - T-bill	2.295	2.353	0.089	0.044	5.259	5.534	1.719	1.773	1.145	1.463	0.542	0.481	-0.020	-1.270	0.004	0.000	0.004	0.012	0.000	0.000	0.000	0.000
Exponential STAR-SRF	2.204	2.284	**-0.014**	-0.101	4.855	5.207	1.680	1.714	0.691	-0.361	0.604	0.571	0.863	0.298	0.001	0.001	0.007	0.026	0.000	0.000	0.000	0.000
Logistic STAR - T-bill	2.442	2.230	-0.053	-0.211	5.960	4.927	1.813	1.675	**-0.028**	-0.284	0.556	0.624	-0.225	1.028	0.000	0.003	0.003	**0.054**	0.000	0.000	0.000	0.000
Logistic STAR-SRF	2.083	2.150	**-0.005**	-0.100	4.340	4.612	1.582	1.627	-0.075	**-0.040**	0.611	0.541	0.313	-0.753	0.002	0.000	0.031	0.026	0.001	0.000	0.006	0.000
TAR-SR	2.221	2.201	0.138	**-0.015**	4.916	4.845	1.737	1.720	-0.036	**-0.046**	0.535	0.556	-1.001	-0.453	0.004	0.002	0.001	0.010	0.000	0.000	0.000	0.000
TAR-SRF	2.236	2.242	0.122	**-0.029**	4.983	5.024	1.694	1.682	**-0.021**	**-0.027**	0.549	0.579	-0.119	0.738	0.000	0.000	0.003	0.020	0.000	0.000	0.000	0.000
Logistic STAR-GARCH(1,1)	2.225	2.154	0.308	0.098	4.857	4.630	1.750	1.684	0.768	0.521	0.514	0.534	-0.407	-0.324	0.001	0.000	0.002	0.015	0.000	0.000	0.000	0.000
MS Two-state homoskedastic	**1.906**	**1.969**	0.171	-0.100	**3.603**	**3.868**	**1.469**	**1.539**	0.805	-0.086	**0.653**	0.632	**2.306**	1.079	**0.112**	**0.032**	**0.598**	**0.828**	**0.546**	**0.427**	**0.469**	**0.615**
MS Two-state heteroskedastic	**1.880**	**1.876**	0.140	0.360	**3.513**	**3.391**	**1.462**	**1.476**	0.831	0.824	**0.667**	**0.805**	**2.554**	**6.569**	**0.143**	**0.446**	**0.873**	**0.349**	**0.171**	0.000	**0.263**	0.000

Table 3 [cont.]

Predictive Accuracy Measures for Stock and Bond Returns

Panel C: United Kingdom 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 D: United Kingdom 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

Table 3 [cont.]

Predictive Accuracy Measures for Stock and Bond Returns

Panel E: Japanese 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	5.126	**4.911**	-0.270	-0.350	26.204	**23.996**	4.119	**3.915**	0.815	1.499	**0.563**	0.534	1.416	0.594	0.004	0.026	**0.925**	**0.631**	**0.099**	**0.651**	**0.210**	**0.646**
Random walk (with drift)	5.110	4.996	-0.353	-0.338	25.987	24.845	4.122	3.992	1.311	1.351	0.521	0.526	N.A.	N.A.	**0.018**	0.032	**0.098**	0.034	**0.062**	0.019	**0.124**	0.047
AR(1)	**5.077**	5.001	-0.334	-0.341	**25.668**	24.891	**4.091**	3.988	1.047	1.268	0.514	0.526	-0.170	N.A.	0.006	0.027	**0.637**	0.049	**0.986**	0.024	**0.735**	**0.057**
Random walk (with drift and GARCH(1,1))	5.143	5.207	-0.699	0.168	25.963	27.080	4.135	4.183	1.552	0.761	0.521	0.368	N.A.	**-3.128**	0.006	**0.099**	**0.318**	**0.372**	**0.196**	0.000	**0.115**	0.000
AR(1) with GARCH(1,1)	5.098	5.161	-0.659	0.192	**25.550**	26.600	4.095	4.165	1.110	0.562	0.521	0.376	0.137	**-2.891**	0.011	**0.052**	**0.458**	**0.497**	**0.855**	0.000	**0.297**	0.000
GARCH(1,1) in mean and exogenous predictors	5.202	4.950	-0.558	**0.019**	26.750	24.505	4.178	3.971	1.401	1.111	0.500	0.579	-0.300	**1.755**	0.001	0.010	**0.849**	**0.803**	0.023	**0.361**	0.033	**0.658**
GARCH(1,1)-in mean and exogenous predictors - t dist.	5.316	5.029	-0.373	0.492	28.117	25.046	4.286	4.078	1.657	**0.391**	0.472	0.504	-1.009	0.225	0.005	0.002	**0.444**	**0.522**	0.000	**0.110**	0.001	**0.148**
EGARCH(1,1)-in mean and exogenous predictors	5.107	5.659	**-0.090**	0.462	26.073	31.811	4.091	4.150	0.970	1.444	0.556	**0.609**	1.258	**2.477**	0.013	0.007	**0.868**	**0.550**	**0.072**	0.000	**0.193**	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	5.360	5.232	0.202	0.710	28.690	26.875	4.337	4.176	2.049	0.654	0.528	0.511	0.647	0.371	0.002	0.001	**0.652**	**0.541**	0.000	0.001	0.000	0.001
TGARCH(1,1)-in mean and exogenous predictors	5.123	**4.913**	-0.230	-0.099	26.195	**24.128**	4.102	3.975	1.216	0.868	0.549	0.556	1.071	1.180	0.010	0.025	**0.949**	**0.992**	**0.063**	**0.398**	**0.152**	**0.681**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.159	5.107	-0.272	0.616	26.541	25.700	4.154	4.156	1.425	**0.367**	0.542	0.504	0.894	0.311	0.003	0.000	**0.864**	**0.669**	0.036	0.017	**0.091**	0.022
Exponential STAR - T-bill	5.265	5.107	-0.123	**0.062**	27.703	26.081	4.187	4.030	0.771	0.719	**0.563**	0.549	1.455	1.067	0.000	0.000	**0.675**	**0.608**	0.002	0.006	0.006	0.022
Exponential STAR-SRF	5.329	5.172	-0.218	-0.222	28.350	26.700	4.316	4.141	1.872	1.797	0.500	0.526	-0.169	0.457	0.000	0.001	**0.617**	**0.673**	0.000	0.001	0.001	0.004
Logistic STAR - T-bill	**4.992**	**4.712**	-0.374	-0.338	**24.782**	**22.091**	**4.019**	**3.770**	1.229	1.208	0.542	0.564	0.882	1.349	**0.051**	**0.104**	**0.655**	**0.533**	**0.214**	**0.581**	**0.309**	**0.612**
Logistic STAR-SRF	5.337	5.233	-0.222	-0.217	28.430	27.342	4.277	4.130	1.258	1.145	0.521	0.549	0.376	0.995	0.000	0.001	**0.684**	**0.668**	0.000	0.000	0.001	0.001
TAR-SR	5.269	5.086	-0.299	-0.237	27.674	25.809	4.110	**3.917**	**0.391**	**0.333**	0.563	**0.602**	1.416	**2.265**	0.001	0.005	**0.730**	**0.792**	0.002	0.009	0.006	0.027
TAR-SRF	5.270	5.184	**-0.107**	**-0.081**	27.762	26.871	4.189	4.052	0.793	0.670	**0.569**	0.586	1.619	**1.926**	0.001	0.001	**0.707**	**0.648**	0.001	0.001	0.005	0.003
Logistic STAR-GARCH(1,1)	5.289	5.108	-0.703	-0.490	27.481	25.855	4.238	4.026	1.545	1.175	0.542	0.526	0.867	0.385	0.007	0.009	**0.961**	**0.951**	0.002	0.006	0.002	0.012
MS Two-state homoskedastic	5.140	5.045	**-0.050**	0.275	26.420	25.376	4.114	3.983	**0.092**	1.903	0.542	**0.586**	0.909	**1.976**	0.016	0.007	**0.817**	**0.577**	0.019	0.027	0.062	**0.071**
MS Two-state heteroskedastic	**5.098**	5.068	-0.144	0.351	25.972	25.565	**4.044**	4.016	**-0.172**	1.938	0.542	0.586	0.909	**2.032**	**0.019**	0.005	**0.934**	**0.551**	**0.059**	0.017	**0.157**	0.043

Panel F: Japanese 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	1.783	1.650	-0.174	-0.260	3.147	2.655	1.258	1.225	0.944	1.559	0.569	0.504	0.790	-1.221	0.000	0.007	**0.109**	**0.072**	0.000	0.000	0.000	0.000
Random walk (with drift)	**1.688**	**1.554**	-0.263	-0.431	**2.779**	**2.228**	**1.204**	**1.126**	1.059	1.075	0.569	0.564	N.A.	N.A.	0.006	**0.010**	**0.502**	**0.326**	**0.624**	**0.505**	**0.155**	0.004
AR(1)	1.691	**1.553**	-0.266	-0.421	2.789	**2.235**	1.204	**1.123**	1.052	1.078	0.569	0.564	N.A.	N.A.	0.000	0.004	**0.992**	**0.644**	**0.852**	**0.996**	**0.167**	0.007
Random walk (with drift and GARCH(1,1))	**1.685**	1.564	-0.269	-0.438	**2.768**	2.254	**1.197**	1.130	0.923	1.023	0.569	0.564	N.A.	N.A.	0.008	0.000	**0.635**	**0.763**	**0.992**	**0.423**	**0.161**	0.003
AR(1) with GARCH(1,1)	**1.687**	**1.552**	-0.263	-0.412	**2.777**	**2.238**	**1.200**	**1.121**	0.938	1.021	0.569	0.564	N.A.	N.A.	0.005	0.004	**0.804**	**0.761**	**0.798**	**0.612**	**0.168**	0.007
GARCH(1,1) in mean and exogenous predictors	1.790	1.656	-0.118	-0.346	3.189	2.623	1.250	1.226	1.007	1.356	**0.590**	0.504	1.456	-1.457	0.001	0.007	**0.051**	**0.077**	0.000	0.000	0.000	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	1.790	1.636	-0.192	**-0.249**	3.168	2.614	1.264	1.221	0.878	1.402	0.583	0.519	1.163	-0.667	0.003	**0.013**	0.043	0.043	0.000	0.000	0.000	0.000
EGARCH(1,1)-in mean and exogenous predictors	1.783	1.632	-0.133	-0.272	3.162	2.590	1.248	1.186	1.004	1.276	0.563	0.526	0.635	-0.215	0.000	0.001	**0.073**	**0.310**	0.000	0.000	0.000	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	1.784	7.407	-0.176	0.385	3.151	54.709	1.260	1.828	0.852	**0.490**	0.542	0.541	-0.151	0.247	0.001	0.007	**0.062**	**0.111**	0.000	0.000	0.000	0.000
TGARCH(1,1)-in mean and exogenous predictors	1.793	1.632	-0.126	**-0.239**	3.199	2.605	1.251	1.210	1.011	1.416	0.590	0.504	1.456	-1.221	0.001	0.001	0.050	**0.158**	0.000	0.000	0.000	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	1.793	1.628	-0.195	-0.316	3.177	2.552	1.270	1.190	0.968	1.412	0.569	0.541	0.676	-0.394	0.004	0.010	0.039	**0.062**	0.000	0.000	0.000	0.000
Exponential STAR - T-bill	1.947	1.875	-0.178	-0.324	3.757	3.412	1.336	1.255	**0.847**	**0.802**	**0.604**	**0.594**	**1.906**	1.615	0.001	0.006	0.039	**0.072**	0.000	0.000	0.000	0.000
Exponential STAR-SRF	1.771	1.610	-0.191	-0.310	3.099	2.497	1.263	1.162	0.999	0.953	0.556	0.571	0.495	0.968	**0.012**	**0.024**	**0.260**	**0.725**	0.000	0.000	0.000	0.000
Logistic STAR - T-bill	1.792	1.711	-0.158	-0.331	3.184	2.818	1.291	1.211	0.850	0.812	0.569	0.571	0.900	0.939	0.002	0.001	**0.133**	**0.148**	0.000	0.000	0.000	0.000
Logistic STAR-SRF	1.917	1.804	**-0.116**	-0.272	3.661	3.179	1.350	1.269	0.907	0.848	0.556	0.571	0.710	1.056	0.000	0.000	**0.053**	**0.169**	0.000	0.000	0.000	0.000
TAR-SR	1.871	1.753	**-0.112**	**-0.239**	3.486	3.016	1.319	1.230	**0.563**	**0.514**	**0.583**	**0.602**	1.361	**1.866**	0.000	0.000	**0.057**	**0.151**	0.000	0.000	0.000	0.000
TAR-SRF	1.820	1.678	-0.131	-0.269	3.297	2.742	1.262	1.176	1.179	1.147	0.542	0.549	0.090	0.339	0.000	0.000	**0.053**	**0.156**	0.000	0.000	0.000	0.000
Logistic STAR-GARCH(1,1)	1.746	2.555	-0.210	-0.531	3.006	6.249	1.230	1.321	1.059	0.820	0.569	**0.586**	0.636	1.373	0.000	0.003	**0.155**	**0.199**	0.001	0.000	0.002	0.000
MS Two-state homoskedastic	1.940	1.670	**-0.071**	-0.304	3.759	2.698	1.391	1.238	**0.778**	1.438	0.528	0.519	0.020	-0.519	**0.013**	0.000	0.011	**0.200**	0.000	0.000	0.000	0.000
MS Two-state heteroskedastic	1.858	1.675	-0.156	-0.317	3.427	2.705	1.354	1.230	1.097	1.577	0.493	0.534	**-1.793**	-0.434	**0.017**	0.006	0.008	**0.078**	0.000	0.000	0.000	0.000

Table 3 [cont.]

Predictive Accuracy Measures for Stock and Bond Returns

Panel G: German 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	**5.642**	5.932	**0.034**	0.170	**31.836**	35.159	4.232	4.546	1.633	0.980	0.625	0.632	**1.684**	0.751	0.032	0.003	**0.824**	**0.124**	**0.769**	**0.076**	**0.955**	**0.196**
Random walk (with drift)	5.745	5.888	**-0.016**	-0.088	33.006	34.664	4.340	4.442	1.571	0.935	**0.639**	**0.647**	N.A.	N.A.	0.007	0.020	**0.215**	**0.064**	**0.208**	**0.059**	**0.452**	**0.164**
AR(1)	5.771	5.878	**-0.004**	-0.079	33.306	34.546	4.381	4.448	1.775	0.901	0.632	0.647	0.671	0.437	0.000	0.000	**0.289**	**0.533**	**0.176**	**0.490**	**0.399**	**0.778**
Random walk (with drift and GARCH(1,1))	5.749	5.903	0.296	**0.004**	32.965	34.843	4.383	4.474	1.404	0.893	0.576	0.632	-0.778	-0.105	0.000	0.004	**0.367**	**0.193**	**0.508**	**0.153**	**0.665**	**0.358**
AR(1) with GARCH(1,1)	5.773	5.879	0.258	**0.004**	33.264	34.564	4.401	4.449	1.655	0.955	0.618	**0.662**	0.803	**1.685**	0.000	0.000	**0.229**	**0.507**	**0.190**	**0.475**	**0.366**	**0.774**
GARCH(1,1) in mean and exogenous predictors	5.650	5.970	0.087	0.394	31.912	35.482	**4.222**	4.583	**0.968**	1.176	**0.639**	0.549	**2.078**	-0.839	0.031	0.002	**0.666**	**0.097**	**0.582**	0.040	**0.844**	**0.090**
GARCH(1,1)-in mean and exogenous predictors - t dist.	5.648	5.925	-0.314	**0.022**	**31.799**	35.110	4.241	4.506	2.494	0.986	0.583	0.602	0.071	-0.560	**0.037**	0.001	**0.945**	**0.186**	**0.459**	**0.099**	**0.610**	**0.254**
EGARCH(1,1)-in mean and exogenous predictors	5.714	6.384	-0.662	-0.125	32.210	40.740	4.262	4.968	3.232	0.985	0.618	0.549	0.803	0.037	0.028	0.010	**0.812**	**0.227**	**0.303**	0.000	**0.225**	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	5.695	6.605	-0.749	0.271	31.877	43.548	**4.187**	5.154	3.906	**0.862**	**0.646**	0.556	1.680	0.499	**0.035**	0.006	**0.631**	**0.149**	**0.410**	0.000	**0.206**	0.000
TGARCH(1,1)-in mean and exogenous predictors	5.727	5.924	-0.444	0.358	32.601	34.961	**4.182**	4.558	4.477	0.908	0.632	0.586	**1.920**	-0.086	0.028	0.000	**0.827**	**0.181**	**0.095**	**0.158**	**0.161**	**0.289**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.735	5.913	-0.726	0.130	32.367	34.944	4.247	4.518	4.395	1.037	0.625	0.602	1.178	0.110	0.028	0.000	**0.864**	**0.240**	**0.185**	**0.164**	**0.131**	**0.366**
Exponential STAR - T-bill	**5.642**	**5.752**	0.034	0.076	31.836	**33.076**	4.232	**4.307**	1.633	**0.750**	0.625	0.647	**1.684**	**1.991**	0.032	**0.039**	**0.824**	**0.896**	**0.769**	**0.994**	**0.955**	**0.989**
Exponential STAR-SRF	5.984	6.146	-0.065	-0.309	35.802	37.681	4.364	4.604	1.622	0.991	0.611	0.594	1.202	0.672	0.001	0.004	**0.168**	**0.272**	0.000	0.000	0.002	0.002
Logistic STAR - T-bill	**5.635**	**5.794**	0.174	0.159	**31.728**	**33.540**	4.276	4.403	2.334	1.240	0.576	0.541	0.459	-0.574	**0.036**	0.029	**0.625**	**0.577**	**0.724**	**0.538**	**0.877**	**0.787**
Logistic STAR-SRF	5.908	5.933	0.123	0.174	34.895	35.174	4.422	4.489	1.755	1.030	0.604	0.617	1.491	**1.716**	0.009	0.020	**0.215**	**0.299**	0.002	0.019	0.007	**0.061**
TAR-SR	5.762	5.828	0.169	0.252	33.174	33.900	4.234	**4.319**	**1.151**	1.206	0.590	0.609	1.300	1.857	0.016	0.026	**0.307**	**0.379**	**0.061**	**0.227**	**0.161**	**0.426**
TAR-SRF	5.755	5.814	0.174	0.293	33.089	33.714	4.300	**4.338**	**1.304**	1.018	0.583	0.594	1.164	1.484	0.020	**0.034**	**0.311**	**0.347**	**0.051**	**0.180**	**0.138**	**0.344**
Logistic STAR-GARCH(1,1)	5.865	**5.708**	-0.373	-0.162	34.258	**32.558**	4.459	4.356	1.880	0.911	0.625	0.624	1.603	1.589	0.031	**0.063**	**0.511**	**0.858**	0.001	**0.287**	0.004	**0.537**
MS Two-state homoskedastic	6.320	5.854	-0.267	-0.208	39.865	34.227	4.650	4.475	1.562	0.985	0.590	**0.647**	0.111	1.400	0.003	0.010	**0.071**	**0.804**	0.000	**0.478**	0.000	**0.715**
MS Two-state heteroskedastic	5.995	5.919	-0.470	0.044	35.723	35.029	4.446	4.499	1.645	**0.880**	0.611	0.609	0.390	0.418	0.000	0.000	**0.175**	**0.276**	0.001	**0.132**	0.002	**0.320**

Panel H: German 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	1.458	1.444	**0.011**	-0.224	2.127	2.036	1.170	1.157	0.792	0.774	**0.681**	0.647	**1.710**	-0.730	0.005	0.005	0.040	0.041	0.014	0.005	0.050	0.004
Random walk (with drift)	1.435	1.405	-0.081	-0.211	2.052	1.929	1.161	1.120	0.832	0.841	0.674	0.654	N.A.	N.A.	0.001	0.001	**0.541**	**0.607**	**0.524**	**0.560**	**0.649**	**0.190**
AR(1)	**1.421**	**1.395**	-0.072	-0.214	**2.014**	**1.899**	**1.133**	**1.112**	0.837	0.802	0.674	0.654	0.527	N.A.	**0.019**	**0.027**	**0.732**	**0.141**	**0.530**	**0.192**	**0.685**	**0.090**
Random walk (with drift and GARCH(1,1))	1.438	1.423	-0.098	-0.247	2.059	1.965	1.160	1.123	0.840	0.874	0.674	0.654	N.A.	N.A.	0.005	0.008	**0.242**	**0.109**	**0.221**	**0.055**	**0.339**	0.021
AR(1) with GARCH(1,1)	**1.423**	1.418	-0.027	-0.253	**2.023**	1.947	**1.138**	1.117	0.857	0.836	0.681	0.654	1.271	N.A.	**0.017**	0.000	**0.512**	**0.391**	**0.403**	**0.226**	**0.685**	**0.058**
GARCH(1,1) in mean and exogenous predictors	1.484	1.461	0.129	-0.213	2.185	2.090	1.201	1.168	0.848	0.870	0.632	0.647	0.243	-0.730	0.002	0.010	0.003	0.011	0.002	0.001	0.005	0.001
GARCH(1,1)-in mean and exogenous predictors - t dist.	1.478	1.454	0.048	-0.292	2.183	2.027	1.189	1.154	0.840	0.780	0.646	0.639	0.258	-1.036	0.001	0.000	0.009	**0.111**	0.002	0.009	0.009	0.002
EGARCH(1,1)-in mean and exogenous predictors	1.496	1.479	0.201	-0.206	2.197	2.144	1.217	1.172	0.872	0.883	0.653	0.647	1.567	-0.046	0.002	0.006	0.001	0.009	0.001	0.000	0.002	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	1.474	1.459	0.150	-0.223	2.151	2.078	1.200	1.156	0.910	0.815	0.646	0.647	0.899	-0.730	0.005	0.006	0.005	0.020	0.006	0.001	0.010	0.001
TGARCH(1,1)-in mean and exogenous predictors	1.477	1.454	0.147	-0.213	2.160	2.068	1.199	1.153	0.837	0.851	0.639	0.639	0.724	-1.036	0.004	0.012	0.004	0.012	0.005	0.001	0.009	0.001
TGARCH(1,1)-in mean and exogenous predictors- t dist.	1.467	1.461	0.063	-0.221	2.148	2.086	1.184	1.168	0.836	0.868	0.646	0.639	0.258	-1.036	0.004	0.014	0.015	0.008	0.007	0.000	0.022	0.000
Exponential STAR - T-bill	1.449	1.423	0.036	-0.117	2.097	2.012	1.149	1.126	0.777	0.835	**0.701**	**0.677**	**2.658**	**2.197**	0.014	0.015	0.049	**0.134**	0.020	0.005	**0.065**	0.013
Exponential STAR-SRF	1.460	1.420	0.021	**-0.070**	2.132	2.012	1.172	1.132	0.787	0.781	0.681	0.647	**1.710**	0.791	0.005	0.004	0.032	**0.089**	0.012	0.013	0.041	0.037
Logistic STAR - T-bill	1.471	**1.392**	0.075	-0.273	2.159	**1.863**	1.187	**1.078**	0.818	**0.531**	0.674	**0.692**	1.458	**2.765**	0.002	**0.069**	0.011	**0.820**	0.006	0.026	0.018	0.006
Logistic STAR-SRF	1.458	1.418	**0.011**	**-0.081**	2.127	2.005	1.170	1.129	0.792	0.786	0.681	0.639	**1.710**	0.374	0.005	0.004	0.040	**0.107**	0.014	0.016	0.050	0.044
TAR-SR	1.527	1.474	0.053	**-0.052**	2.330	2.171	1.207	1.160	**0.706**	**0.723**	0.639	0.639	0.419	0.822	0.001	0.005	0.001	0.016	0.000	0.000	0.000	0.000
TAR-SRF	1.549	1.538	**0.001**	-0.106	2.401	2.354	1.216	1.204	0.816	0.857	0.646	0.624	1.162	0.806	0.001	0.000	0.001	0.004	0.000	0.000	0.000	0.000
Logistic STAR-GARCH(1,1)	**1.425**	**1.386**	-0.037	-0.127	**2.030**	**1.906**	**1.129**	**1.095**	0.830	0.837	**0.694**	**0.669**	**2.388**	**1.876**	**0.028**	0.028	**0.249**	**0.509**	**0.104**	**0.126**	**0.254**	**0.178**
MS Two-state homoskedastic	1.546	1.869	-0.022	-0.543	2.390	3.197	1.256	1.452	**0.570**	1.357	0.646	0.579	1.033	**-1.689**	0.000	**0.042**	0.001	0.000	0.000	0.000	0.000	0.000
MS Two-state heteroskedastic	1.490	1.583	-0.033	-0.314	2.220	2.407	1.206	1.259	**0.663**	**0.588**	0.639	0.632	0.061	0.986	0.003	0.008	0.012	0.034	0.001	0.000	0.003	0.000

Table 3 [cont.]

Predictive Accuracy Measures for Stock and Bond Returns

Panel I: French 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	**5.642**	5.932	**0.034**	0.170	**31.836**	35.159	4.232	4.546	1.633	0.980	0.625	0.632	**1.684**	0.751	0.032	0.003	**0.824**	**0.124**	**0.769**	**0.076**	**0.955**	**0.196**
Random walk (with drift)	5.745	5.888	**-0.016**	-0.088	33.006	34.664	4.340	4.442	1.571	0.935	**0.639**	**0.647**	N.A.	N.A.	0.007	0.020	**0.215**	**0.064**	**0.208**	**0.059**	**0.452**	**0.164**
AR(1)	5.771	5.878	**-0.004**	-0.079	33.306	34.546	4.381	4.448	1.775	0.901	0.632	0.647	0.671	0.437	0.000	0.000	**0.289**	**0.533**	**0.176**	**0.490**	**0.399**	**0.778**
Random walk (with drift and GARCH(1,1))	5.749	5.903	0.296	**0.004**	32.965	34.843	4.383	4.474	1.404	0.893	0.576	0.632	-0.778	-0.105	0.000	0.004	**0.367**	**0.193**	**0.508**	**0.153**	**0.665**	**0.358**
AR(1) with GARCH(1,1)	5.773	5.879	0.258	**0.004**	33.264	34.564	4.401	4.449	1.655	0.955	0.618	**0.662**	0.803	**1.685**	0.000	0.000	**0.229**	**0.507**	**0.190**	**0.475**	**0.366**	**0.774**
GARCH(1,1) in mean and exogenous predictors	5.650	5.970	0.087	0.394	31.912	35.482	**4.222**	4.583	**0.968**	1.176	**0.639**	0.549	**2.078**	-0.839	0.031	0.002	**0.666**	**0.097**	**0.582**	0.040	**0.844**	**0.090**
GARCH(1,1)-in mean and exogenous predictors - t dist.	5.648	5.925	-0.314	**0.022**	**31.799**	35.110	4.241	4.506	2.494	0.986	0.583	0.602	0.071	-0.560	**0.037**	0.001	**0.945**	**0.186**	**0.459**	**0.099**	**0.610**	**0.254**
EGARCH(1,1)-in mean and exogenous predictors	5.714	6.384	-0.662	-0.125	32.210	40.740	4.262	4.968	3.232	0.985	0.618	0.549	0.803	0.037	0.028	0.010	**0.812**	**0.227**	**0.303**	0.000	**0.225**	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	5.695	6.605	-0.749	0.271	31.877	43.548	**4.187**	5.154	3.906	**0.862**	**0.646**	0.556	1.680	0.499	**0.035**	0.006	**0.631**	**0.149**	**0.410**	0.000	**0.206**	0.000
TGARCH(1,1)-in mean and exogenous predictors	5.727	5.924	-0.444	0.358	32.601	34.961	**4.182**	4.558	4.477	0.908	0.632	0.586	**1.920**	-0.086	0.028	0.000	**0.827**	**0.181**	**0.095**	**0.158**	**0.161**	**0.289**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.735	5.913	-0.726	0.130	32.367	34.944	4.247	4.518	4.395	1.037	0.625	0.602	1.178	0.110	0.028	0.000	**0.864**	**0.240**	**0.185**	**0.164**	**0.131**	**0.366**
Exponential STAR - T-bill	**5.642**	**5.752**	0.034	0.076	31.836	**33.076**	4.232	**4.307**	1.633	**0.750**	0.625	0.647	**1.684**	**1.991**	0.032	**0.039**	**0.824**	**0.896**	**0.769**	**0.994**	**0.955**	**0.989**
Exponential STAR-SRF	5.984	6.146	-0.065	-0.309	35.802	37.681	4.364	4.604	1.622	0.991	0.611	0.594	1.202	0.672	0.001	0.004	**0.168**	**0.272**	0.000	0.000	0.002	0.002
Logistic STAR - T-bill	**5.635**	**5.794**	0.174	0.159	**31.728**	**33.540**	4.276	4.403	2.334	1.240	0.576	0.541	0.459	-0.574	**0.036**	0.029	**0.625**	**0.577**	**0.724**	**0.538**	**0.877**	**0.787**
Logistic STAR-SRF	5.908	5.933	0.123	0.174	34.895	35.174	4.422	4.489	1.755	1.030	0.604	0.617	1.491	**1.716**	0.009	0.020	**0.215**	**0.299**	0.002	0.019	0.007	**0.061**
TAR-SR	5.762	5.828	0.169	0.252	33.174	33.900	4.234	**4.319**	**1.151**	1.206	0.590	0.609	1.300	1.857	0.016	0.026	**0.307**	**0.379**	**0.061**	**0.227**	**0.161**	**0.426**
TAR-SRF	5.755	5.814	0.174	0.293	33.089	33.714	4.300	**4.338**	**1.304**	1.018	0.583	0.594	1.164	1.484	0.020	**0.034**	**0.311**	**0.347**	**0.051**	**0.180**	**0.138**	**0.344**
Logistic STAR-GARCH(1,1)	5.865	**5.708**	-0.373	-0.162	34.258	**32.558**	4.459	4.356	1.880	0.911	0.625	0.624	1.603	1.589	0.031	**0.063**	**0.511**	**0.858**	0.001	**0.287**	0.004	**0.537**
MS Two-state homoskedastic	6.320	5.854	-0.267	-0.208	39.865	34.227	4.650	4.475	1.562	0.985	0.590	**0.647**	0.111	1.400	0.003	0.010	**0.071**	**0.804**	0.000	**0.478**	0.000	**0.715**
MS Two-state heteroskedastic	5.995	5.919	-0.470	0.044	35.723	35.029	4.446	4.499	1.645	**0.880**	0.611	0.609	0.390	0.418	0.000	0.000	**0.175**	**0.276**	0.001	**0.132**	0.002	**0.320**

Panel J: French 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	1.578	**1.509**	-0.115	-0.287	2.476	2.194	1.262	1.208	-1.582	**1.607**	0.632	**0.662**	0.556	N.A.	0.023	0.001	0.012	**0.131**	0.000	0.025	0.000	0.007
Random walk (with drift)	**1.504**	**1.525**	-0.313	-0.475	**2.164**	**2.101**	1.192	**1.198**	3.345	3.992	**0.674**	**0.662**	N.A.	N.A.	0.016	0.006	**0.234**	**0.525**	**0.301**	**0.696**	0.025	0.001
AR(1)	1.506	**1.522**	-0.255	-0.489	2.204	**2.079**	**1.185**	**1.195**	4.437	3.909	**0.674**	**0.662**	N.A.	N.A.	0.006	**0.023**	**0.453**	**0.174**	**0.139**	**0.311**	0.042	0.000
Random walk (with drift and GARCH(1,1))	**1.478**	1.530	-0.136	-0.488	**2.167**	**2.103**	**1.188**	**1.199**	2.800	4.186	**0.674**	0.662	N.A.	N.A.	0.008	0.006	**0.867**	**0.874**	**0.654**	**0.638**	**0.496**	0.001
AR(1) with GARCH(1,1)	**1.487**	1.542	-0.150	-0.504	**2.189**	2.124	**1.184**	1.207	3.862	4.339	0.674	0.662	N.A.	N.A.	0.007	0.001	**0.460**	**0.734**	**0.225**	**0.362**	**0.232**	0.000
GARCH(1,1) in mean and exogenous predictors	1.570	1.565	**-0.050**	-0.383	2.462	2.301	1.246	1.230	-1.294	**0.962**	0.646	0.662	0.899	N.A.	0.021	0.004	0.007	0.030	0.000	0.001	0.000	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	1.541	1.551	**-0.069**	-0.408	2.371	2.240	1.231	1.225	-0.820	2.163	0.646	0.662	0.605	N.A.	0.024	0.003	0.019	**0.066**	0.000	0.004	0.000	0.000
EGARCH(1,1)-in mean and exogenous predictors	1.547	1.587	-0.232	-0.373	2.339	2.380	1.231	1.274	0.166	2.728	0.660	0.662	1.510	N.A.	**0.035**	0.001	**0.091**	0.023	0.000	0.000	0.000	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	1.590	1.571	-0.361	-0.387	2.399	2.320	1.243	1.241	**-0.210**	3.274	0.667	0.654	1.090	-0.718	0.019	0.003	**0.106**	0.028	0.000	0.000	0.000	0.000
TGARCH(1,1)-in mean and exogenous predictors	1.598	1.555	-0.175	-0.402	2.522	2.257	1.259	1.227	-1.354	2.181	0.646	0.662	0.757	N.A.	0.019	0.000	0.014	**0.108**	0.000	0.003	0.000	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	1.587	1.557	-0.374	-0.393	2.380	2.272	1.242	1.225	0.542	2.734	0.660	0.662	0.515	N.A.	0.020	0.007	**0.129**	0.029	0.000	0.001	0.000	0.000
Exponential STAR - T-bill	1.635	1.681	-0.181	-0.199	2.641	2.788	1.297	1.335	-1.690	-2.170	0.639	0.624	1.246	0.971	**0.056**	**0.026**	0.014	0.012	0.000	0.000	0.000	0.000
Exponential STAR-SRF	1.555	1.625	-0.120	**-0.080**	2.403	2.633	1.235	1.290	-1.055	-2.163	0.625	0.609	0.394	0.394	**0.028**	0.009	0.023	0.005	0.000	0.000	0.000	0.000
Logistic STAR - T-bill	1.578	1.541	-0.115	-0.170	2.476	2.347	1.262	1.231	-1.582	**-1.142**	0.632	0.609	0.556	0.254	0.023	**0.027**	0.012	**0.057**	0.000	0.000	0.000	0.000
Logistic STAR-SRF	1.623	1.687	-0.142	-0.238	2.615	2.790	1.288	1.342	**0.527**	3.083	0.660	0.632	1.271	0.488	0.017	0.003	0.006	0.005	0.000	0.000	0.000	0.000
TAR-SR	1.633	1.641	-0.153	-0.192	2.642	2.655	1.322	1.316	-1.842	-2.527	0.646	0.624	1.285	0.971	0.017	0.010	0.006	0.010	0.000	0.000	0.000	0.000
TAR-SRF	1.588	1.610	-0.090	**-0.103**	2.512	2.582	1.266	1.278	-0.607	-1.730	0.646	0.647	1.285	1.481	0.026	0.007	0.008	0.006	0.000	0.000	0.000	0.000
Logistic STAR-GARCH(1,1)	1.578	1.600	-0.115	**-0.141**	2.476	2.539	1.262	1.279	-1.582	-2.283	0.632	0.617	0.556	0.419	0.023	0.010	0.012	0.011	0.000	0.000	0.000	0.000
MS Two-state homoskedastic	1.652	1.559	**-0.078**	-0.519	2.724	2.162	1.304	1.226	**0.288**	4.779	0.653	0.662	1.333	N.A.	0.000	0.003	0.001	**0.521**	0.000	**0.067**	0.000	0.000
MS Two-state heteroskedastic	1.633	1.527	-0.201	-0.261	2.626	2.262	1.310	1.212	0.723	3.904	0.653	0.662	0.274	N.A.	0.000	0.013	0.002	0.012	0.000	0.001	0.000	0.001

Table 3 [cont.]

Predictive Accuracy Measures for Stock and Bond Returns

Panel K: Canadian 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	4.396	4.660	0.574	0.559	18.995	21.404	3.367	3.538	0.828	**0.436**	0.583	0.624	0.761	**1.755**	0.022	0.003	0.026	0.005	0.038	0.001	0.034	0.002
Random walk (with drift)	4.353	4.470	**0.138**	**0.191**	18.932	19.945	**3.218**	**3.314**	1.061	1.043	**0.653**	**0.654**	N.A.	N.A.	0.021	0.043	**0.053**	0.009	**0.056**	0.010	**0.149**	0.032
AR(1)	**4.335**	4.503	**0.135**	0.209	18.773	20.230	**3.206**	3.343	0.963	0.880	**0.660**	**0.654**	1.376	0.462	0.004	0.000	**0.912**	**0.097**	**0.990**	**0.099**	**0.933**	**0.221**
Random walk (with drift and GARCH(1,1))	4.367	4.463	**0.098**	0.199	19.065	19.881	**3.226**	**3.305**	1.027	1.049	**0.653**	0.654	N.A.	N.A.	0.009	0.002	**0.083**	**0.377**	**0.087**	**0.415**	**0.221**	**0.629**
AR(1) with GARCH(1,1)	4.362	4.519	0.150	**0.193**	19.006	20.383	3.229	3.338	0.997	0.894	0.653	**0.669**	N.A.	1.691	0.001	0.001	**0.220**	**0.062**	**0.247**	**0.052**	**0.469**	**0.133**
GARCH(1,1) in mean and exogenous predictors	4.450	4.635	0.526	0.468	19.529	21.267	3.440	3.509	0.856	**0.456**	0.556	0.617	0.010	1.092	0.012	0.002	0.019	0.008	0.010	0.002	0.013	0.004
GARCH(1,1)-in mean and exogenous predictors - t dist.	4.355	4.608	0.321	0.331	18.860	21.127	3.348	3.473	0.823	0.580	0.590	0.617	0.346	0.504	0.026	0.002	**0.080**	0.012	0.049	0.003	**0.097**	0.009
EGARCH(1,1)-in mean and exogenous predictors	4.370	4.808	0.602	**0.116**	18.734	23.108	3.336	3.623	0.902	0.714	0.549	0.624	-0.740	1.145	0.019	0.011	0.037	0.003	**0.165**	0.000	**0.097**	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	**4.300**	4.699	0.276	0.258	**18.416**	22.014	3.284	3.533	0.877	1.063	0.625	0.579	1.114	-0.306	**0.035**	0.004	**0.169**	0.006	**0.182**	0.000	**0.306**	0.001
TGARCH(1,1)-in mean and exogenous predictors	4.401	4.706	0.568	0.502	19.044	21.896	3.388	3.536	0.989	**0.498**	0.521	0.632	-1.121	1.414	0.017	0.011	0.027	0.002	0.048	0.000	0.043	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	4.347	4.627	0.285	0.409	18.816	21.244	3.348	3.494	0.961	0.615	0.590	0.639	0.226	1.483	0.027	0.002	**0.097**	0.009	**0.058**	0.002	**0.122**	0.005
Exponential STAR - T-bill	4.647	4.515	0.853	0.770	20.871	19.788	3.447	3.371	**0.652**	0.620	0.646	0.632	**2.065**	**1.999**	0.033	**0.048**	0.004	0.016	0.000	0.012	0.000	0.006
Exponential STAR-SRF	4.401	**4.460**	0.541	0.618	19.080	**19.510**	3.377	3.423	0.799	0.681	0.590	0.586	0.897	1.047	0.022	0.031	0.027	0.045	0.027	**0.144**	0.029	**0.096**
Logistic STAR - T-bill	**4.257**	**4.277**	0.380	0.319	**17.975**	**18.195**	3.258	**3.270**	0.785	0.632	0.604	0.609	1.174	1.363	**0.053**	**0.082**	**0.161**	**0.488**	**0.335**	**0.957**	**0.356**	**0.692**
Logistic STAR-SRF	4.378	**4.433**	0.663	0.772	**18.724**	**19.055**	3.279	3.385	1.150	1.605	0.632	0.617	**2.212**	**2.111**	**0.072**	**0.095**	0.014	0.015	0.002	0.005	0.002	0.003
TAR-SR	4.431	4.493	0.589	0.649	19.290	19.767	3.393	3.458	**0.751**	0.719	0.597	0.579	1.238	1.019	0.020	0.028	0.018	0.032	0.013	**0.066**	0.013	0.046
TAR-SRF	4.528	4.546	0.474	0.505	20.279	20.415	3.359	3.453	**0.741**	0.672	0.576	0.564	0.519	0.418	0.009	0.020	0.014	0.035	0.001	0.010	0.001	0.017
Logistic STAR-GARCH(1,1)	4.504	4.575	0.427	0.866	20.103	20.183	3.468	3.552	1.114	0.848	0.556	0.556	-0.225	0.510	0.009	0.026	0.018	0.011	0.001	0.016	0.003	0.005
MS Two-state homoskedastic	4.577	5.135	0.502	1.622	20.699	23.743	3.456	3.932	1.188	0.856	0.583	0.436	0.080	-0.531	0.004	0.010	0.009	0.019	0.000	0.000	0.000	0.000
MS Two-state heteroskedastic	4.650	4.851	0.694	0.875	21.138	22.767	3.581	3.700	1.018	0.805	0.569	0.496	0.603	-0.402	0.001	0.005	0.003	0.004	0.000	0.000	0.000	0.000

Panel L: Canadian 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	1.804	1.751	0.331	-0.067	3.144	3.060	1.387	1.390	0.600	0.708	0.597	0.647	0.408	0.791	0.000	0.001	0.000	0.006	0.000	0.000	0.000	0.001
Random walk (with drift)	**1.692**	1.703	-0.189	-0.355	**2.826**	2.775	**1.356**	1.346	**0.420**	**0.333**	**0.667**	**0.654**	N.A.	N.A.	0.002	0.001	**0.806**	**0.883**	**0.856**	**0.983**	**0.404**	**0.054**
AR(1)	1.695	1.705	-0.177	-0.352	**2.841**	2.784	**1.358**	1.353	0.447	0.338	**0.667**	0.654	N.A.	N.A.	0.000	0.000	**0.579**	**0.692**	**0.459**	**0.570**	**0.347**	0.049
Random walk (with drift and GARCH(1,1))	**1.686**	1.717	**-0.013**	-0.363	**2.843**	2.817	1.358	1.374	0.557	**0.295**	0.667	0.654	N.A.	N.A.	0.000	0.000	**0.418**	**0.373**	**0.397**	**0.176**	**0.694**	0.020
AR(1) with GARCH(1,1)	**1.691**	**1.695**	**-0.024**	-0.330	2.859	**2.765**	1.358	1.361	0.556	0.356	0.667	0.654	N.A.	N.A.	0.000	0.006	**0.255**	**0.970**	**0.220**	**0.692**	**0.464**	**0.074**
GARCH(1,1) in mean and exogenous predictors	1.735	1.784	0.058	-0.082	3.007	3.176	1.388	1.419	0.592	0.673	0.653	0.632	0.000	0.309	0.000	0.004	0.006	0.002	0.003	0.000	0.012	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	1.765	1.765	0.101	-0.116	3.104	3.101	1.400	1.392	0.546	0.467	0.653	0.654	0.640	0.946	0.001	0.005	0.001	0.004	0.000	0.000	0.001	0.000
EGARCH(1,1)-in mean and exogenous predictors	1.767	1.818	0.306	**-0.022**	3.027	3.304	1.387	1.444	0.745	0.465	0.667	0.609	**2.268**	0.042	0.001	0.006	0.000	0.000	0.002	0.000	0.001	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	1.776	1.824	0.145	-0.051	3.132	3.324	1.386	1.438	0.544	0.438	0.653	0.617	0.938	0.223	0.003	0.005	0.000	0.001	0.000	0.000	0.000	0.000
TGARCH(1,1)-in mean and exogenous predictors	1.798	1.792	0.258	-0.125	3.166	3.196	1.392	1.420	0.608	0.578	0.611	0.624	0.153	0.094	0.001	0.006	0.000	0.002	0.000	0.000	0.000	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	1.786	1.771	0.275	-0.090	3.113	3.128	1.384	1.401	0.606	0.470	0.618	0.654	0.453	1.066	0.000	0.004	0.000	0.003	0.000	0.000	0.000	0.000
Exponential STAR - T-bill	1.824	1.825	0.067	**0.022**	3.323	3.331	1.409	1.398	**0.150**	**0.142**	0.611	0.602	0.567	0.896	0.005	0.006	0.001	0.002	0.000	0.000	0.000	0.000
Exponential STAR-SRF	1.897	1.903	0.138	0.086	3.581	3.613	1.468	1.446	**0.397**	0.364	0.618	0.571	0.717	-0.175	0.002	0.002	0.000	0.000	0.000	0.000	0.000	0.000
Logistic STAR - T-bill	1.794	1.761	0.119	0.027	3.203	3.099	1.372	**1.331**	0.598	0.551	**0.688**	**0.662**	**2.438**	**1.869**	0.000	0.002	0.000	0.006	0.000	0.000	0.000	0.001
Logistic STAR-SRF	1.701	**1.653**	0.047	**0.005**	2.890	**2.731**	**1.340**	**1.300**	0.437	0.452	0.660	0.624	1.393	0.552	**0.013**	**0.040**	0.049	**0.189**	0.028	**0.079**	**0.084**	**0.212**
TAR-SR	1.770	1.754	0.267	0.232	3.062	3.024	1.372	1.344	0.536	0.483	0.639	0.624	1.633	1.557	**0.027**	**0.032**	0.000	0.002	0.000	0.000	0.000	0.000
TAR-SRF	1.845	1.809	0.299	0.221	3.316	3.224	1.460	1.427	0.656	0.640	0.583	0.571	0.389	0.205	0.003	0.011	0.000	0.001	0.000	0.000	0.000	0.000
Logistic STAR-GARCH(1,1)	1.702	**1.665**	**-0.047**	-0.170	2.893	**2.743**	1.372	**1.334**	0.456	0.406	0.653	**0.662**	-0.359	1.381	**0.007**	**0.022**	**0.105**	**0.646**	0.041	**0.270**	**0.117**	**0.274**
MS Two-state homoskedastic	1.876	1.776	0.279	-0.212	3.439	3.109	1.513	1.436	0.644	0.461	0.632	0.639	1.374	-0.409	0.000	0.002	0.000	0.008	0.000	0.000	0.000	0.000
MS Two-state heteroskedastic	1.868	1.803	0.313	-0.224	3.390	3.202	1.494	1.434	0.619	0.869	0.632	0.639	1.484	-0.409	0.001	0.007	0.000	0.002	0.000	0.000	0.000	0.000

Table 3 [cont.]

Predictive Accuracy Measures for Stock and Bond Returns

Panel K: Italian 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	6.181	6.440	1.073	**-0.034**	37.055	41.477	4.742	4.708	0.979	1.509	0.549	0.519	1.440	-0.454	0.011	0.001	0.046	0.044	**0.057**	0.000	0.019	0.001
Random walk (with drift)	**6.068**	**6.103**	-0.415	-0.260	**36.652**	37.182	**4.622**	**4.577**	1.167	1.184	**0.590**	**0.609**	N.A.	N.A.	0.006	0.013	**0.275**	**0.136**	**0.240**	**0.122**	**0.359**	**0.267**
AR(1)	6.143	**6.082**	**-0.361**	-0.242	37.603	**36.931**	4.720	**4.543**	1.129	1.240	0.563	**0.609**	-1.237	N.A.	0.002	0.002	**0.144**	**0.869**	0.034	**0.754**	**0.083**	**0.858**
Random walk (with drift and GARCH(1,1))	**6.074**	6.142	**-0.249**	**0.002**	**36.827**	37.721	**4.635**	4.608	1.126	1.141	**0.576**	0.609	-1.187	N.A.	0.002	**0.038**	**0.282**	0.007	**0.212**	0.006	**0.406**	0.021
AR(1) with GARCH(1,1)	**6.133**	**6.088**	**-0.250**	**0.047**	37.551	**37.057**	4.713	**4.536**	1.133	1.211	0.549	**0.617**	-1.685	1.253	0.004	0.001	**0.107**	**0.530**	0.033	**0.512**	**0.091**	**0.802**
GARCH(1,1) in mean and exogenous predictors	6.201	6.364	0.594	0.226	38.097	40.445	4.765	4.619	1.082	1.423	0.569	0.579	1.209	0.986	0.018	0.001	**0.100**	0.042	0.003	0.001	0.007	0.002
GARCH(1,1)-in mean and exogenous predictors - t dist.	6.193	6.420	0.920	0.624	37.510	40.826	4.734	4.656	1.011	1.428	0.563	0.549	1.465	0.532	**0.023**	0.001	**0.059**	0.031	0.008	0.000	0.006	0.001
EGARCH(1,1)-in mean and exogenous predictors	6.445	6.912	1.213	-0.115	40.061	47.757	4.953	5.129	0.880	1.853	0.535	0.519	1.035	-0.635	0.003	0.000	0.049	0.045	0.000	0.000	0.000	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	6.182	6.948	0.850	0.469	37.501	48.048	**4.665**	5.188	0.870	1.809	**0.576**	0.586	**1.745**	1.211	0.019	0.000	**0.067**	0.040	0.011	0.000	0.010	0.000
TGARCH(1,1)-in mean and exogenous predictors	6.588	6.345	0.762	0.208	42.816	40.210	5.053	4.627	0.907	1.534	0.514	0.549	0.064	0.456	0.000	0.000	**0.056**	**0.064**	0.000	0.001	0.000	0.004
TGARCH(1,1)-in mean and exogenous predictors- t dist.	6.424	6.338	0.868	0.716	40.519	39.653	4.921	4.620	0.749	1.422	0.535	0.564	0.787	0.972	0.004	0.001	**0.060**	0.045	0.000	0.002	0.000	0.004
Exponential STAR - T-bill	6.350	6.341	1.166	1.333	38.959	38.435	4.803	4.784	**0.737**	**0.671**	0.507	0.481	0.354	-0.425	0.008	**0.017**	0.045	0.023	0.001	0.007	0.001	0.001
Exponential STAR-SRF	7.249	6.265	1.687	1.326	49.697	37.491	5.242	4.701	0.846	0.975	0.500	0.549	0.603	1.539	**0.031**	0.014	0.026	0.023	0.000	**0.058**	0.000	0.008
Logistic STAR - T-bill	6.303	6.524	1.946	2.511	**35.946**	**36.256**	4.896	5.089	**0.725**	**0.612**	0.535	0.489	**2.367**	1.437	**0.033**	**0.037**	0.007	0.002	**0.113**	**0.121**	0.000	0.000
Logistic STAR-SRF	6.463	6.523	1.570	1.792	39.305	39.336	5.117	5.023	**0.486**	**0.523**	0.431	0.444	-0.827	-0.451	0.000	0.001	**0.067**	0.030	0.001	0.004	0.000	0.000
TAR-SR	6.430	6.480	1.199	1.459	39.905	39.861	4.853	4.837	0.798	0.681	0.514	0.556	0.684	1.676	0.000	0.002	**0.055**	0.028	0.000	0.001	0.000	0.000
TAR-SRF	6.445	6.538	1.508	1.770	39.260	39.612	5.116	5.188	1.189	1.127	0.424	0.414	-1.687	-1.693	0.015	0.005	0.029	0.022	0.000	0.002	0.000	0.000
Logistic STAR-GARCH(1,1)	6.184	6.360	1.104	1.420	37.023	38.437	4.758	4.819	0.960	0.964	0.549	0.534	1.507	1.265	0.013	0.012	0.043	0.022	**0.052**	0.010	0.015	0.001
MS Two-state homoskedastic	6.331	6.436	0.671	0.794	39.629	40.794	4.761	4.710	1.126	1.331	0.479	0.549	-0.758	0.683	0.001	0.000	**0.052**	0.032	0.001	0.000	0.001	0.001
MS Two-state heteroskedastic	6.195	6.403	1.025	0.581	37.331	40.660	4.668	4.625	0.974	1.428	0.521	0.549	0.570	0.379	0.006	0.001	**0.052**	0.030	0.045	0.000	0.018	0.001

Panel L: Italian 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	1.892	1.835	-0.292	-0.433	**3.496**	3.180	1.379	1.373	1.869	**0.967**	0.694	0.677	0.133	-0.951	0.061	0.002	**0.877**	**0.073**	**0.209**	0.001	**0.082**	0.000
Random walk (with drift)	1.937	1.770	-0.328	-0.455	3.645	2.925	1.396	1.325	1.644	1.835	**0.701**	**0.692**	N.A.	N.A.	0.020	0.003	**0.182**	**0.805**	**0.229**	**0.959**	**0.062**	0.011
AR(1)	**1.876**	1.785	-0.235	-0.454	**3.463**	2.981	**1.361**	1.337	2.464	1.340	0.688	**0.692**	-0.929	N.A.	**0.062**	0.009	**0.836**	**0.121**	**0.597**	**0.069**	**0.283**	0.002
Random walk (with drift and GARCH(1,1))	1.892	1.785	-0.131	-0.540	3.562	2.895	**1.364**	1.342	**1.364**	2.058	**0.701**	**0.692**	N.A.	N.A.	0.033	0.015	**0.697**	**0.379**	**0.887**	**0.602**	**0.705**	0.002
AR(1) with GARCH(1,1)	1.917	1.801	**-0.044**	-0.512	3.675	2.980	1.392	1.352	2.798	1.872	0.694	0.692	1.176	N.A.	0.043	0.000	**0.095**	**0.347**	0.016	**0.146**	**0.051**	0.001
GARCH(1,1) in mean and exogenous predictors	1.987	1.832	-0.176	-0.504	3.916	3.103	1.489	1.360	1.771	1.593	0.688	0.677	0.934	-0.951	0.025	0.007	0.043	**0.201**	0.000	0.004	0.001	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	**1.877**	1.847	-0.089	-0.324	3.517	3.305	**1.370**	1.374	2.075	**0.047**	**0.701**	0.677	1.281	-0.951	0.059	0.001	**0.405**	0.008	**0.152**	0.000	**0.304**	0.000
EGARCH(1,1)-in mean and exogenous predictors	2.009	1.934	**-0.040**	-0.281	4.036	3.663	1.458	1.550	2.121	1.467	0.653	0.609	-0.043	-0.541	0.015	0.014	0.008	0.006	0.000	0.000	0.000	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	1.935	1.831	**-0.029**	**-0.144**	3.743	3.330	1.403	1.415	2.648	**0.993**	0.674	0.632	0.010	-0.538	0.031	0.013	**0.059**	0.010	0.009	0.000	0.033	0.000
TGARCH(1,1)-in mean and exogenous predictors	2.009	1.809	-0.203	-0.462	3.994	3.061	1.520	1.358	1.542	1.981	0.667	0.677	0.075	-0.256	0.019	0.015	0.031	**0.275**	0.000	0.006	0.000	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	**1.882**	1.800	-0.085	-0.288	3.536	3.156	1.385	1.376	1.956	1.560	0.681	0.684	-0.491	0.453	0.052	0.006	**0.424**	**0.063**	**0.184**	0.001	**0.357**	0.001
Exponential STAR - T-bill	2.004	1.781	-0.263	-0.339	3.947	3.057	1.509	1.378	2.552	2.983	0.674	0.692	-0.309	1.041	0.044	0.060	**0.060**	**0.185**	0.000	0.000	0.000	0.000
Exponential STAR-SRF	1.877	**1.716**	-0.305	-0.420	**3.430**	**2.767**	1.383	**1.290**	1.692	1.924	0.694	0.684	0.133	-0.670	**0.078**	**0.068**	**0.984**	**0.826**	**0.239**	**0.203**	**0.074**	0.008
Logistic STAR - T-bill	1.982	1.769	-0.290	-0.408	3.846	2.962	1.489	1.366	1.862	2.342	0.646	0.662	-1.043	-0.368	0.047	0.058	**0.113**	**0.399**	0.000	0.003	0.000	0.000
Logistic STAR-SRF	1.977	**1.715**	-0.343	-0.417	3.792	**2.768**	1.469	**1.282**	2.691	2.095	0.681	0.684	0.711	-0.670	**0.069**	**0.065**	**0.170**	**0.769**	0.000	**0.272**	0.000	0.010
TAR-SR	1.968	1.717	-0.255	-0.358	3.808	2.819	1.462	1.318	2.070	2.335	0.632	0.632	0.112	-0.301	0.051	**0.087**	**0.112**	**0.585**	0.000	0.010	0.001	0.002
TAR-SRF	2.414	1.897	-0.392	-0.410	5.672	3.432	1.612	1.446	2.073	2.422	0.632	0.624	-1.030	-0.964	0.015	0.028	0.001	0.043	0.000	0.000	0.000	0.000
Logistic STAR-GARCH(1,1)	1.891	**1.713**	-0.274	-0.399	3.502	**2.775**	1.376	**1.279**	1.834	2.060	0.694	0.684	0.133	-0.670	0.061	0.064	**0.806**	**0.843**	**0.185**	**0.238**	**0.092**	0.013
MS Two-state homoskedastic	1.995	1.947	-0.293	**-0.252**	3.894	3.727	1.486	1.418	**-0.108**	3.847	0.688	0.639	0.726	**-1.815**	0.042	0.005	**0.091**	0.000	0.000	0.000	0.000	0.000
MS Two-state heteroskedastic	2.120	1.723	-0.213	**-0.207**	4.449	2.924	1.514	1.314	**0.512**	2.138	0.646	0.669	-1.423	-0.535	0.004	0.018	0.002	**0.473**	0.000	**0.163**	0.000	**0.145**

Table 4

Diebold-Mariano and Giacomini-White Equal Predictive Accuracy Tests: Stock Return Forecasts

Panel A: United States Stock Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.368	0.402	0.442	0.441	0.765	0.808	0.122	0.709	0.195	0.806	0.955	0.391	0.730	0.207	0.914	0.881	0.920	**0.000**	**0.004**
Random walk (with drift)	0.251		0.719	0.883	0.732	0.713	0.805	0.306	0.750	0.314	0.800	0.930	0.632	0.731	0.632	0.912	0.881	0.887	**0.000**	**0.003**
AR(1)	0.213	0.577		0.666	0.684	0.693	0.789	0.272	0.727	0.288	0.786	0.924	0.598	0.709	0.598	0.902	0.880	0.884	**0.000**	**0.002**
Random walk (with drift and GARCH(1,1))	0.083	0.396	0.506		0.506	0.670	0.763	0.251	0.697	0.269	0.761	0.918	0.558	0.681	0.558	0.897	0.880	0.866	**0.000**	**0.001**
AR(1) with GARCH(1,1)	0.067	0.835	0.915	0.920		0.673	0.760	0.250	0.695	0.260	0.760	0.916	0.559	0.681	0.559	0.889	0.880	0.881	**0.000**	**0.001**
GARCH(1,1) in mean and exogenous predictors	0.328	0.747	0.794	0.720	0.829		0.621	0.064	0.513	0.068	0.630	0.896	0.235	0.499	0.235	0.847	0.880	0.783	**0.000**	**0.003**
GARCH(1,1)-in mean and exogenous predictors - t dist	0.297	0.697	0.732	0.757	0.768	0.841		0.085	0.251	0.161	0.574	0.917	0.192	0.323	0.192	0.897	0.876	0.559	**0.001**	**0.010**
EGARCH(1,1)-in mean and exogenous predictors	0.214	0.704	0.608	0.669	0.550	0.308	0.176		0.881	0.417	0.898	0.979	0.878	0.935	0.878	0.948	0.886	0.970	**0.004**	**0.021**
EGARCH(1,1)-in mean and exogenous predictors- t dis	0.256	0.798	0.822	0.864	0.810	0.867	0.851	0.206		0.189	0.735	0.960	0.291	0.480	0.291	0.934	0.878	0.681	**0.000**	**0.006**
TGARCH(1,1)-in mean and exogenous predictors	0.367	0.621	0.579	0.572	0.519	0.156	0.383	0.804	0.430		0.832	0.960	0.805	0.862	0.805	0.916	0.888	0.961	**0.004**	**0.018**
TGARCH(1,1)-in mean and exogenous predictors- t dis	0.435	0.688	0.735	0.758	0.762	0.803	0.728	0.254	0.664	0.385		0.904	0.194	0.312	0.194	0.895	0.876	0.544	**0.001**	**0.010**
Exponential STAR - T-bill	0.260	0.167	0.208	0.220	0.259	0.436	0.127	0.140	0.147	0.241	0.118		**0.045**	0.067	**0.045**	0.566	0.867	0.237	**0.000**	**0.001**
Exponential STAR-SRF	0.889	0.251	0.212	0.083	0.067	0.329	0.297	0.214	0.257	0.367	0.435	0.260		0.730	0.607	0.914	0.881	0.920	**0.000**	**0.004**
Logistic STAR - T-bill	0.275	0.794	0.854	0.883	0.799	0.670	0.195	**0.035**	0.483	0.256	0.273	0.187	0.275		0.270	0.902	0.879	0.707	**0.000**	**0.005**
Logistic STAR-SRF	0.708	0.251	0.213	0.083	0.067	0.328	0.297	0.214	0.256	0.367	0.435	0.260	0.894	0.275		0.914	0.881	0.920	**0.000**	**0.004**
TAR-SR	0.242	0.325	0.308	0.325	0.279	0.050	0.333	0.284	0.351	0.247	0.325	0.545	0.242	0.457	0.242		0.866	0.262	**0.001**	**0.004**
TAR-SRF	0.214	0.181	0.175	0.185	0.168	0.419	0.504	1.000	0.510	1.000	0.403	0.193	0.213	0.258	0.214	0.452		0.124	0.090	0.095
Logistic STAR-GARCH(1,1)	0.304	0.452	0.489	0.507	0.499	0.126	0.679	0.136	0.416	0.071	0.761	0.285	0.304	0.547	0.304	0.401	0.432		**0.000**	**0.000**
MS Two-state homoskedastic	**0.005**	**0.003**	**0.002**	**0.001**	**0.001**	**0.005**	**0.011**	**0.041**	**0.002**	**0.043**	**0.011**	**0.003**	**0.005**	**0.005**	**0.005**	**0.012**	**0.026**	**0.001**		0.795
MS Two-state heteroskedastic	**0.043**	**0.032**	**0.027**	**0.021**	**0.017**	**0.037**	0.083	0.130	0.057	0.127	0.082	**0.015**	**0.043**	0.052	**0.043**	**0.046**	**0.037**	**0.009**	0.585	

Panel B: United States Stock Returns, 12-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		**0.042**	0.062	**0.034**	0.053	0.549	0.353	0.629	0.880	0.369	0.516	0.206	**0.031**	0.123	**0.031**	0.407	0.874	0.130	**0.001**	**0.001**
Random walk (with drift)	1.000		0.877	0.321	0.855	0.980	0.996	1.000	0.927	0.947	0.983	0.983	0.429	0.678	0.427	0.861	0.883	0.733	**0.008**	**0.015**
AR(1)	1.000	0.480		0.096	0.526	0.972	0.999	0.984	0.918	0.931	0.988	0.816	0.184	0.417	0.183	0.743	0.882	0.631	**0.007**	**0.011**
Random walk (with drift and GARCH(1,1))	1.000	0.979	0.431		0.900	0.987	0.998	0.999	0.928	0.958	0.986	0.988	0.446	0.689	0.444	0.854	0.883	0.750	**0.007**	**0.013**
AR(1) with GARCH(1,1)	1.000	0.624	0.837	0.466		0.985	0.999	0.967	0.919	0.944	0.981	0.806	0.179	0.418	0.178	0.724	0.882	0.641	**0.004**	**0.007**
GARCH(1,1) in mean and exogenous predictors	0.359	0.240	0.101	0.183	0.055		0.288	0.623	0.882	0.311	0.494	0.164	**0.012**	0.092	**0.012**	0.398	0.874	0.092	**0.000**	**0.000**
GARCH(1,1)-in mean and exogenous predictors - t dist	**0.003**	0.185	0.107	0.176	0.122	0.698		0.764	0.889	0.562	0.791	0.185	**0.002**	0.069	**0.002**	0.438	0.875	0.204	**0.001**	**0.002**
EGARCH(1,1)-in mean and exogenous predictors	0.344	0.091	0.226	0.078	1.000	0.329	0.686		0.874	0.350	0.341	0.080	**0.009**	**0.018**	**0.009**	0.144	0.867	0.184	**0.003**	**0.006**
EGARCH(1,1)-in mean and exogenous predictors- t dis	0.557	0.319	0.374	0.308	0.375	0.555	0.524	0.585		0.115	0.122	0.085	0.075	0.073	0.075	0.104	0.784	0.100	**0.015**	**0.021**
TGARCH(1,1)-in mean and exogenous predictors	0.391	0.364	0.387	0.358	0.374	0.193	0.225	0.622	0.549		0.614	0.239	**0.022**	0.123	**0.022**	0.436	0.877	0.153	**0.001**	**0.001**
TGARCH(1,1)-in mean and exogenous predictors- t dis	0.374	0.278	0.236	0.262	0.274	0.862	0.816	0.502	0.574	**0.000**		0.132	**0.002**	0.058	**0.002**	0.382	0.875	0.160	**0.003**	**0.003**
Exponential STAR - T-bill	0.668	1.000	**0.000**	**0.000**	0.569	0.352	0.495	0.399	0.377	1.000	0.352		**0.029**	0.050	**0.029**	0.613	0.877	0.435	**0.001**	**0.002**
Exponential STAR-SRF	0.333	0.370	0.430	0.325	0.323	0.228	0.181	0.227	0.310	0.285	0.191	0.260		0.747	0.097	0.851	0.886	0.837	**0.010**	**0.014**
Logistic STAR - T-bill	0.342	0.571	0.571	1.000	1.000	0.431	0.754	0.233	0.315	0.575	0.426	0.159	0.463		0.250	0.820	0.883	0.662	**0.008**	**0.014**
Logistic STAR-SRF	0.333	0.369	0.428	0.323	0.322	0.229	0.181	0.227	0.309	0.285	0.191	0.259	0.503	0.463		0.851	0.886	0.838	**0.010**	**0.014**
TAR-SR	0.513	0.610	0.620	0.624	0.461	0.341	0.484	0.359	0.533	0.419	0.587	0.686	0.604	0.651	0.603		0.871	0.395	**0.018**	**0.026**
TAR-SRF	0.535	0.233	0.531	0.221	0.541	0.525	0.599	0.368	0.378	0.535	0.555	0.458	0.298	0.074	0.303	0.611		0.120	0.096	0.097
Logistic STAR-GARCH(1,1)	0.387	0.817	0.838	0.787	0.915	0.378	0.463	0.468	0.444	0.454	0.447	0.479	0.439	**0.011**	0.442	0.678	0.578		**0.001**	**0.000**
MS Two-state homoskedastic	0.179	0.247	0.244	0.234	0.224	0.161	0.183	0.174	0.119	0.171	0.207	0.135	0.218	0.170	0.219	0.239	**0.000**	0.149		0.794
MS Two-state heteroskedastic	0.170	0.274	0.268	0.261	0.244	0.156	0.190	0.159	0.132	0.174	0.211	0.128	0.268	0.211	0.270	0.251	1.000	0.134	0.712	

Table 4 [cont.]

Diebold-Mariano and Giacomini-White Equal Predictive Accuracy Tests: Stock Return Forecasts

Panel C: United Kingdom Stock Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
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)	0.941		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)	0.940	0.071		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))	0.921	0.194	0.067		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)	0.985	0.389	0.636	0.608		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	0.130	0.445	0.454	0.439	0.408		**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	0.387	0.228	0.207	0.207	0.207	0.142		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	0.835	0.071	0.100	0.058	0.075	0.542	**0.042**		**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 dis	0.910	0.301	0.328	0.281	0.302	0.306	0.423	**0.027**		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	0.692	0.107	0.133	0.086	0.137	0.562	**0.002**	0.732	0.098		**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 dis	0.746	0.509	0.488	0.494	0.517	0.144	0.739	0.070	0.214	**0.012**		0.463	0.730	0.272	0.735	0.971	0.912	0.949	**0.000**	**0.031**
Exponential STAR - T-bill	0.493	0.882	0.848	0.891	0.822	0.062	0.439	0.647	0.871	0.556	0.926		0.735	0.301	0.889	0.936	0.993	0.978	**0.000**	**0.016**
Exponential STAR-SRF	0.939	0.665	0.699	0.624	0.592	0.280	0.393	0.957	0.762	0.820	0.746	0.741		0.187	0.432	0.719	0.780	0.669	**0.000**	**0.013**
Logistic STAR - T-bill	0.085	0.328	0.309	0.321	0.315	0.090	0.153	0.203	0.233	0.185	0.132	0.265	0.198		0.801	0.883	0.937	0.924	**0.037**	0.157
Logistic STAR-SRF	0.207	1.000	0.996	0.998	0.980	0.130	0.316	0.870	0.815	0.749	0.647	0.394	0.982	0.081		0.920	0.924	0.897	**0.000**	**0.005**
TAR-SR	0.236	0.097	0.097	0.069	0.122	0.243	**0.004**	0.883	0.326	0.392	0.113	0.297	0.798	0.164	0.347		0.648	0.426	**0.000**	**0.002**
TAR-SRF	0.085	0.168	0.174	0.155	0.139	0.321	**0.028**	0.443	0.120	0.399	0.068	0.064	0.095	0.073	0.103	0.124		0.279	**0.000**	**0.002**
Logistic STAR-GARCH(1,1)	0.178	0.730	0.739	0.731	0.865	0.453	0.066	0.988	0.490	0.930	0.224	0.153	0.387	0.163	0.414	0.961	0.478		**0.000**	**0.001**
MS Two-state homoskedastic	**0.000**	**0.001**	**0.001**	**0.001**	**0.001**	**0.000**	**0.003**	**0.000**	**0.001**	**0.001**	**0.001**	**0.000**	**0.000**	0.117	**0.000**	**0.000**	**0.000**	**0.000**		0.871
MS Two-state heteroskedastic	**0.047**	0.076	0.068	0.080	0.074	**0.021**	0.286	0.091	0.173	0.067	0.188	0.104	0.085	0.517	**0.047**	**0.027**	**0.019**	**0.012**	0.530	

Panel D: United Kingdom Stock Returns, 12-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
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)	0.155		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)	0.147	0.403		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))	0.151	0.570	0.455		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)	0.161	0.327	0.230	0.416		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	0.380	0.111	0.154	0.096	0.161		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	0.497	0.084	0.165	0.071	0.133	0.784		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	0.359	0.277	0.298	0.274	0.291	0.356	0.335		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 dis	0.333	0.271	0.292	0.268	0.281	0.351	0.320	0.455		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	**0.034**	0.087	0.149	0.083	0.124	**0.023**	0.065	0.442	0.387		**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 dis	0.844	0.142	0.243	0.122	0.180	0.757	0.813	0.354	0.370	0.249		0.198	0.436	0.088	0.423	0.335	0.430	0.836	**0.001**	**0.000**
Exponential STAR - T-bill	0.637	0.902	0.935	0.877	0.964	0.456	0.567	0.303	0.307	0.481	0.434		1.000	0.224	0.994	0.804	0.988	0.992	**0.000**	**0.000**
Exponential STAR-SRF	0.580	0.742	0.847	0.722	0.826	0.363	0.502	0.411	0.385	0.337	0.386	0.066		0.050	0.446	0.404	0.334	0.947	**0.000**	**0.000**
Logistic STAR - T-bill	0.331	0.161	0.467	**0.033**	0.227	0.317	0.265	0.185	0.255	0.273	0.201	0.619	0.236		0.977	0.957	0.956	0.973	**0.000**	**0.001**
Logistic STAR-SRF	0.203	0.286	0.389	0.280	0.348	0.202	0.240	0.367	0.391	0.166	0.201	0.271	0.197	0.302		0.467	0.507	0.999	**0.000**	**0.000**
TAR-SR	0.738	0.534	0.428	0.568	0.388	0.841	0.883	0.336	0.403	0.634	0.916	0.619	0.733	0.359	0.370		0.542	0.885	**0.000**	**0.000**
TAR-SRF	0.234	0.329	0.279	0.315	0.298	0.211	0.271	0.447	0.371	0.229	0.229	0.252	0.198	0.075	0.066	0.111		0.930	**0.000**	**0.000**
Logistic STAR-GARCH(1,1)	0.587	0.511	0.594	0.506	0.537	0.575	0.567	0.365	0.175	0.629	0.541	0.108	0.422	0.249	1.000	0.407	0.427		**0.001**	**0.001**
MS Two-state homoskedastic	0.146	**0.046**	0.150	0.054	0.109	0.114	0.126	0.202	0.145	0.109	0.118	0.123	0.123	0.129	0.139	0.137	0.065	0.105		0.542
MS Two-state heteroskedastic	0.154	0.154	0.175	0.152	0.167	0.129	0.141	0.181	0.143	0.119	0.134	0.117	0.112	0.150	0.124	0.125	0.081	0.068	0.435	

Table 4 [cont.]

Diebold-Mariano and Giacomini-White Equal Predictive Accuracy Tests: Stock Return Forecasts

Panel E: Japanese Stock Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.430	0.287	0.564	0.386	0.852	0.975	0.416	0.967	0.487	0.673	0.908	0.971	0.270	0.975	0.902	0.922	0.904	0.543	0.413
Random walk (with drift)	0.773		0.108	0.845	0.401	0.822	0.933	0.491	0.913	0.542	0.672	0.904	0.946	0.268	0.937	0.836	0.852	0.884	0.588	0.466
AR(1)	0.295	0.355		0.939	0.738	0.914	0.964	0.602	0.944	0.658	0.795	0.944	0.964	0.330	0.960	0.885	0.896	0.925	0.702	0.569
Random walk (with drift and GARCH(1,1))	0.905	0.194	0.128		0.136	0.724	0.882	0.398	0.863	0.442	0.554	0.833	0.905	0.211	0.895	0.762	0.783	0.845	0.492	0.374
AR(1) with GARCH(1,1)	0.266	0.924	0.741	0.382		0.883	0.941	0.531	0.918	0.587	0.726	0.908	0.942	0.293	0.938	0.842	0.857	0.912	0.648	0.503
GARCH(1,1) in mean and exogenous predictors	0.305	0.313	0.338	0.538	0.256		0.912	0.120	0.871	0.126	0.190	0.680	0.887	0.139	0.904	0.662	0.720	0.856	0.293	0.172
GARCH(1,1)-in mean and exogenous predictors - t dist	0.072	0.117	0.146	0.192	0.222	0.355		**0.002**	0.672	**0.003**	**0.012**	0.373	0.548	0.054	0.578	0.384	0.329	0.418	0.120	0.066
EGARCH(1,1)-in mean and exogenous predictors	0.977	0.837	0.876	0.903	0.960	0.536	**0.007**		0.992	0.731	0.874	0.845	0.962	0.298	0.974	0.855	0.910	0.905	0.612	0.470
EGARCH(1,1)-in mean and exogenous predictors- t dis	0.135	0.268	0.234	0.353	0.310	0.417	0.883	**0.035**		**0.014**	**0.039**	0.288	0.424	0.093	0.436	0.242	0.258	0.354	0.117	0.073
TGARCH(1,1)-in mean and exogenous predictors	0.976	0.610	0.789	0.833	0.921	0.528	**0.009**	0.652	0.051		0.885	0.815	0.952	0.272	0.969	0.827	0.886	0.908	0.558	0.413
TGARCH(1,1)-in mean and exogenous predictors- t dis	0.512	0.602	0.630	0.898	0.607	0.391	**0.036**	0.515	0.201	0.254		0.779	0.931	0.205	0.948	0.770	0.818	0.877	0.437	0.295
Exponential STAR - T-bill	0.396	0.395	0.414	0.490	1.000	0.455	0.389	0.593	0.467	0.661	0.723		0.665	0.129	0.674	0.513	0.513	0.554	0.237	0.164
Exponential STAR-SRF	0.151	0.222	0.180	0.331	0.249	0.462	0.983	0.190	0.880	0.236	0.325	0.843		**0.025**	0.559	0.367	0.315	0.375	0.142	0.081
Logistic STAR - T-bill	0.545	0.335	**0.044**	0.466	0.062	0.437	0.232	0.855	0.407	0.830	0.557	0.268	0.149		0.957	0.816	0.880	0.937	0.735	0.676
Logistic STAR-SRF	0.107	0.239	0.197	0.335	0.244	0.364	0.935	0.109	0.978	0.141	0.218	0.783	0.934	0.239		0.345	0.268	0.350	0.131	0.072
TAR-SR	0.087	0.175	0.099	0.244	0.106	0.532	0.546	0.374	0.302	0.398	0.321	**0.012**	0.598	0.536	0.604		0.502	0.539	0.237	0.163
TAR-SRF	0.279	0.403	0.352	0.552	0.450	0.642	0.576	0.169	0.358	0.072	0.089	0.395	0.798	0.474	0.653	0.661		0.554	0.227	0.140
Logistic STAR-GARCH(1,1)	0.362	0.404	0.343	0.520	0.345	0.457	0.900	0.241	0.322	0.418	0.536	0.285	0.772	0.282	0.617	0.730	0.864		0.168	0.095
MS Two-state homoskedastic	0.358	0.959	0.846	0.930	0.847	0.134	0.458	0.754	0.378	0.459	0.616	0.855	0.321	0.297	0.506	0.373	0.453	0.416		0.167
MS Two-state heteroskedastic	0.717	0.773	0.671	0.825	0.767	0.180	0.261	0.956	0.269	0.726	0.723	0.681	0.311	0.613	0.328	0.266	0.349	0.260	0.213	

Panel F: Japanese Stock Returns, 12-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.847	0.854	0.983	0.979	0.918	0.894	0.872	0.989	0.524	0.983	0.891	0.924	**0.000**	0.898	0.781	0.796	0.824	0.834	0.941
Random walk (with drift)	0.396		0.775	0.974	0.955	0.250	0.628	0.840	0.943	0.156	0.906	0.898	0.924	**0.000**	0.870	0.699	0.748	0.758	0.744	0.996
AR(1)	0.413	0.876		0.973	0.949	0.236	0.608	0.837	0.930	0.155	0.888	0.887	0.919	**0.001**	0.868	0.688	0.745	0.755	0.724	0.998
Random walk (with drift and GARCH(1,1))	0.238	0.325	0.573		0.104	**0.012**	**0.001**	0.744	0.556	**0.015**	0.055	**0.034**	0.314	**0.011**	0.571	0.095	0.459	0.251	**0.000**	**0.000**
AR(1) with GARCH(1,1)	0.269	0.393	0.461	0.335		**0.014**	**0.001**	0.767	0.669	**0.014**	0.175	0.189	0.540	**0.011**	0.652	0.248	0.536	0.386	**0.000**	**0.000**
GARCH(1,1) in mean and exogenous predictors	0.211	0.678	0.658	0.247	0.263		0.845	0.858	0.977	0.195	0.983	0.871	0.929	**0.000**	0.896	0.753	0.777	0.793	0.781	0.910
GARCH(1,1)-in mean and exogenous predictors - t dist	0.335	0.825	0.827	0.155	0.111	0.607		0.823	0.912	0.088	0.964	0.736	0.865	**0.029**	0.848	0.653	0.711	0.660	0.563	0.677
EGARCH(1,1)-in mean and exogenous predictors	0.549	0.598	0.600	0.648	0.424	0.525	0.600		0.219	0.125	0.200	0.195	0.238	0.071	0.275	0.202	0.263	0.221	0.180	0.192
EGARCH(1,1)-in mean and exogenous predictors- t dis	0.210	0.371	0.409	0.476	0.410	0.277	0.371	0.737		**0.004**	0.172	0.225	0.391	**0.000**	0.501	0.236	0.446	0.332	0.102	0.141
TGARCH(1,1)-in mean and exogenous predictors	0.772	0.531	0.541	0.271	0.265	0.103	0.354	0.518	0.179		0.989	0.898	0.914	**0.000**	0.891	0.785	0.790	0.806	0.865	0.967
TGARCH(1,1)-in mean and exogenous predictors- t dis	0.249	0.458	0.496	0.329	0.504	0.219	0.286	0.692	0.161	0.243		0.502	0.709	**0.006**	0.751	0.435	0.617	0.503	0.199	0.251
Exponential STAR - T-bill	0.394	0.577	0.593	0.204	0.178	0.473	0.639	0.659	0.653	0.192	0.877		1.000	**0.017**	0.878	0.426	0.653	0.503	**0.000**	**0.000**
Exponential STAR-SRF	0.447	0.439	0.471	0.376	0.453	0.445	0.472	**0.000**	0.525	0.475	0.626	1.000		0.051	0.800	0.065	0.531	0.271	**0.000**	**0.000**
Logistic STAR - T-bill	1.000	0.146	0.173	0.253	0.186	1.000	0.648	0.412	0.072	1.000	**0.000**	0.145	0.370		0.926	0.918	0.855	0.897	0.998	1.000
Logistic STAR-SRF	0.514	0.515	0.537	0.448	0.466	0.526	0.504	1.000	0.712	0.534	0.643	1.000	0.709	0.424		0.068	0.326	0.146	**0.002**	**0.026**
TAR-SR	0.300	0.264	0.251	0.233	0.236	0.317	0.571	0.638	0.214	0.313	0.339	0.299	0.531	0.188	0.482		0.721	0.550	**0.000**	0.423
TAR-SRF	0.671	0.711	0.751	0.370	0.397	0.648	0.512	0.802	0.830	0.665	0.478	0.402	0.066	0.570	0.271	**0.005**		0.301	0.260	0.306
Logistic STAR-GARCH(1,1)	0.631	0.559	0.597	0.389	0.445	0.606	0.441	0.721	0.394	0.677	0.347	0.166	0.491	0.404	0.381	0.849	0.833		0.297	0.357
MS Two-state homoskedastic	0.383	0.904	0.916	**0.033**	1.000	0.215	0.126	0.480	0.183	0.190	0.084	0.571	0.702	**0.000**	1.000	0.273	0.808	0.746		0.747
MS Two-state heteroskedastic	0.261	0.353	0.299	**0.028**	1.000	0.167	0.196	0.507	0.271	0.200	0.072	0.575	0.625	**0.004**	0.199	0.513	0.853	0.771	0.787	

Table 4 [cont.]

Diebold-Mariano and Giacomini-White Equal Predictive Accuracy Tests: Stock Return Forecasts

Panel G: German Stock Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.884	0.946	0.845	0.907	0.576	0.530	0.849	0.748	0.752	0.839	0.349	0.846	0.463	0.975	0.813	0.886	0.938	0.992	0.984
Random walk (with drift)	0.494		0.688	0.530	0.647	0.156	0.146	0.382	0.325	0.451	0.467	0.116	0.762	0.161	0.858	0.548	0.531	0.749	0.983	0.970
AR(1)	0.271	0.432		0.360	0.523	0.101	0.130	0.298	0.268	0.387	0.396	0.054	0.732	0.094	0.812	0.470	0.451	0.718	0.987	0.938
Random walk (with drift and GARCH(1,1))	0.609	0.822	0.914		0.686	0.165	0.160	0.384	0.334	0.445	0.460	0.155	0.744	0.193	0.852	0.537	0.518	0.748	0.980	0.950
AR(1) with GARCH(1,1)	0.341	0.355	0.483	0.518		0.118	0.147	0.313	0.283	0.389	0.400	0.093	0.721	0.129	0.807	0.464	0.445	0.717	0.984	0.916
GARCH(1,1) in mean and exogenous predictors	0.214	0.564	0.457	0.609	0.487		0.486	0.851	0.748	0.745	0.849	0.424	0.834	0.440	0.991	0.780	0.927	0.941	0.987	0.976
GARCH(1,1)-in mean and exogenous predictors - t dist	0.912	0.423	0.401	0.458	0.466	0.642		0.874	0.878	0.777	0.919	0.470	0.830	0.460	0.982	0.783	0.886	0.927	0.985	0.976
EGARCH(1,1)-in mean and exogenous predictors	0.303	0.804	0.779	0.922	0.570	0.191	0.256		0.324	0.549	0.615	0.151	0.786	0.252	0.966	0.631	0.677	0.813	0.982	0.953
EGARCH(1,1)-in mean and exogenous predictors- t dis	0.366	0.841	0.716	0.859	0.617	0.139	0.276	0.790		0.628	0.793	0.252	0.797	0.318	0.961	0.674	0.732	0.822	0.982	0.967
TGARCH(1,1)-in mean and exogenous predictors	0.849	0.136	0.642	0.265	0.864	0.848	0.392	0.289	0.232		0.545	0.248	0.763	0.275	0.874	0.589	0.575	0.761	0.980	0.920
TGARCH(1,1)-in mean and exogenous predictors- t dis	0.649	0.882	0.865	0.628	0.915	0.497	0.190	0.915	0.678	0.288		0.161	0.761	0.227	0.900	0.564	0.567	0.762	0.972	0.934
Exponential STAR - T-bill	0.784	0.494	0.271	0.609	0.341	0.214	0.912	0.303	0.366	0.849	0.649		0.846	0.463	0.975	0.813	0.886	0.938	0.992	0.984
Exponential STAR-SRF	0.147	0.416	1.000	0.323	**0.001**	0.139	0.561	0.213	0.220	0.739	0.742	0.147		0.146	0.415	0.273	0.266	0.350	0.787	0.512
Logistic STAR - T-bill	0.847	0.623	0.304	0.553	0.429	0.986	0.990	0.743	0.782	0.730	0.791	0.847	0.525		0.935	0.794	0.798	0.916	0.995	0.988
Logistic STAR-SRF	0.155	0.391	0.388	0.357	0.347	0.070	0.063	0.102	0.150	0.476	0.382	0.155	0.135	0.319		0.220	**0.012**	0.408	0.895	0.664
TAR-SR	0.669	0.732	0.898	0.886	0.983	0.706	0.662	0.653	0.540	0.805	0.958	0.669	0.389	0.583	0.565		0.482	0.697	0.994	0.899
TAR-SRF	0.475	0.929	0.830	0.958	0.854	0.212	0.472	0.336	0.520	0.772	0.939	0.475	0.663	0.752	**0.045**	0.805		0.775	0.963	0.891
Logistic STAR-GARCH(1,1)	0.200	0.511	0.334	0.407	0.298	0.178	0.217	0.349	0.523	0.728	0.562	0.200	0.130	0.284	0.464	0.360	0.316		0.927	0.726
MS Two-state homoskedastic	0.068	0.068	**0.040**	0.054	**0.035**	0.089	0.108	0.112	0.117	**0.047**	0.158	0.068	0.515	0.052	0.457	0.060	0.179	0.334		0.071
MS Two-state heteroskedastic	0.088	0.195	0.292	0.287	0.409	0.140	0.138	0.201	0.179	0.275	0.247	0.088	0.104	0.105	0.827	0.462	0.428	0.577	0.350	

Panel H: French Stock Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.173	0.204	0.304	0.367	0.932	0.726	0.948	0.696	0.983	0.883	**0.019**	0.384	**0.014**	0.999	0.998	0.942	0.436	0.934	0.920
Random walk (with drift)	0.492		0.670	0.856	0.980	0.948	0.886	0.963	0.884	0.980	0.947	0.280	0.561	0.192	0.999	0.993	0.979	0.831	0.976	0.982
AR(1)	0.327	0.521		0.672	0.893	0.940	0.861	0.965	0.869	0.977	0.945	0.222	0.535	0.122	0.999	0.995	0.991	0.800	0.985	0.990
Random walk (with drift and GARCH(1,1))	0.839	0.552	0.474		0.776	0.911	0.804	0.930	0.789	0.957	0.905	0.210	0.497	0.156	0.999	0.987	0.940	0.698	0.961	0.953
AR(1) with GARCH(1,1)	0.756	0.111	0.092	0.225		0.895	0.764	0.920	0.760	0.949	0.876	0.144	0.460	0.097	0.999	0.987	0.937	0.633	0.958	0.956
GARCH(1,1) in mean and exogenous predictors	0.097	0.083	**0.019**	0.340	0.059		**0.015**	0.644	0.160	0.790	0.258	**0.009**	0.181	**0.011**	0.994	0.921	0.507	0.066	0.802	0.681
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.248	0.175	**0.040**	0.656	0.126	**0.043**		0.937	0.501	0.992	0.793	**0.022**	0.302	**0.025**	0.997	0.983	0.779	0.271	0.896	0.841
EGARCH(1,1)-in mean and exogenous predictors	0.128	**0.048**	**0.019**	0.184	0.055	0.288	**0.044**		0.093	0.574	0.162	**0.005**	0.166	**0.003**	0.994	0.857	0.414	0.052	0.781	0.627
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.657	0.429	0.371	0.376	0.745	0.168	0.204	0.180		0.939	0.711	**0.018**	0.289	**0.006**	0.996	0.964	0.777	0.303	0.897	0.850
TGARCH(1,1)-in mean and exogenous predictors	**0.041**	0.107	**0.027**	0.225	0.112	0.304	0.077	0.329	0.323		**0.041**	**0.002**	0.114	**0.004**	0.992	0.858	0.349	**0.016**	0.759	0.587
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.454	0.177	0.055	0.377	0.219	0.250	0.431	0.172	0.724	**0.020**		**0.010**	0.254	**0.010**	0.997	0.967	0.678	0.110	0.877	0.775
Exponential STAR - T-bill	0.130	0.769	0.779	0.526	0.591	0.051	0.071	**0.026**	0.131	**0.022**	0.081		0.698	0.368	1.000	1.000	0.999	0.979	0.983	0.987
Exponential STAR-SRF	0.954	0.609	0.992	0.997	0.997	0.290	0.212	0.086	0.329	0.332	0.799	0.871		0.241	0.986	0.935	0.802	0.614	0.909	0.854
Logistic STAR - T-bill	0.064	0.449	0.253	0.534	0.257	0.068	0.107	**0.027**	**0.017**	**0.041**	0.072	0.898	0.762		1.000	0.999	0.998	0.985	0.997	1.000
Logistic STAR-SRF	**0.015**	**0.002**	**0.009**	**0.006**	**0.013**	**0.037**	**0.018**	**0.027**	**0.030**	0.067	**0.034**	**0.007**	0.069	**0.001**		**0.010**	**0.003**	**0.001**	**0.030**	**0.010**
TAR-SR	**0.013**	**0.034**	**0.020**	0.079	**0.047**	0.393	0.149	0.586	0.234	0.613	0.155	**0.005**	0.171	**0.010**	0.074		0.077	**0.002**	0.535	0.304
TAR-SRF	0.056	0.060	**0.025**	0.164	0.166	0.507	0.339	0.556	0.488	0.513	0.369	**0.010**	0.660	**0.023**	**0.026**	0.143		0.053	0.864	0.710
Logistic STAR-GARCH(1,1)	0.945	0.484	0.286	0.837	0.732	0.087	0.244	0.125	0.587	**0.036**	0.451	0.143	0.959	0.066	**0.015**	**0.012**	0.051		0.937	0.922
MS Two-state homoskedastic	0.262	0.124	0.084	0.161	0.187	0.463	0.353	0.485	0.402	0.573	0.389	0.106	0.401	**0.029**	0.190	0.619	0.281	0.251		0.248
MS Two-state heteroskedastic	0.317	0.104	0.065	0.217	0.214	0.538	0.408	0.470	0.465	0.765	0.635	0.098	0.541	**0.008**	0.051	0.593	0.396	0.305	0.518	

Table 4 [cont.]

Diebold-Mariano and Giacomini-White Equal Predictive Accuracy Tests: Stock Return Forecasts

Panel I: Canadian Stock Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.403	0.356	0.436	0.423	0.902	0.210	0.351	**0.039**	0.530	0.158	0.839	0.684	**0.024**	0.434	0.730	0.941	0.954	0.888	0.931
Random walk (with drift)	0.103		0.161	0.897	0.695	0.745	0.504	0.553	0.346	0.625	0.483	0.784	0.611	0.242	0.542	0.659	0.904	0.813	0.976	0.987
AR(1)	**0.000**	0.335		0.952	0.940	0.797	0.556	0.616	0.391	0.679	0.537	0.800	0.659	0.272	0.576	0.699	0.932	0.851	0.992	0.994
Random walk (with drift and GARCH(1,1))	0.201	0.194	**0.030**		0.319	0.711	0.466	0.508	0.311	0.586	0.443	0.770	0.578	0.219	0.517	0.629	0.879	0.787	0.968	0.986
AR(1) with GARCH(1,1)	0.090	0.811	**0.042**	0.126		0.726	0.480	0.524	0.322	0.600	0.457	0.773	0.591	0.226	0.526	0.639	0.887	0.798	0.972	0.990
GARCH(1,1) in mean and exogenous predictors	0.379	1.000	1.000	**0.021**	1.000		**0.013**	0.090	**0.001**	0.209	**0.003**	0.764	0.130	**0.003**	0.283	0.402	0.880	0.785	0.822	0.905
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.602	0.283	1.000	0.427	0.240	**0.048**		0.604	0.060	0.747	0.371	0.851	0.826	0.086	0.570	0.826	0.992	0.993	0.942	0.978
EGARCH(1,1)-in mean and exogenous predictors	0.740	0.128	1.000	0.480	0.364	0.404	0.420		**0.035**	0.732	0.334	0.831	0.690	**0.004**	0.520	0.746	0.975	0.961	0.945	0.965
EGARCH(1,1)-in mean and exogenous predictors- t dist.	**0.003**	1.000	1.000	0.164	1.000	**0.014**	0.297	**0.029**		0.950	0.946	0.883	0.978	0.206	0.708	0.935	0.999	1.000	0.982	0.991
TGARCH(1,1)-in mean and exogenous predictors	0.870	0.348	0.507	0.476	0.552	0.484	0.728	0.139	0.272		0.198	0.825	0.505	**0.005**	0.425	0.661	0.983	0.897	0.893	0.918
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.607	1.000	1.000	0.298	**0.035**	**0.034**	0.154	**0.001**	0.075	0.459		0.852	0.876	0.088	0.594	0.845	0.998	0.996	0.956	0.982
Exponential STAR - T-bill	0.618	0.688	0.669	0.692	0.685	0.675	0.585	0.645	0.493	0.649	0.587		0.167	0.100	0.141	0.149	0.330	0.298	0.419	0.502
Exponential STAR-SRF	0.876	0.145	**0.011**	0.217	0.118	0.475	0.559	0.826	**0.009**	0.832	0.543	0.628		**0.012**	0.415	0.694	0.936	0.953	0.886	0.926
Logistic STAR - T-bill	0.145	1.000	1.000	0.076	**0.042**	**0.040**	0.386	**0.034**	0.663	0.061	0.384	0.400	0.097		0.824	0.965	1.000	0.999	0.989	0.989
Logistic STAR-SRF	0.795	0.093	0.058	0.091	0.074	0.676	0.474	0.570	0.197	0.857	0.827	0.573	0.580	0.662		0.680	0.897	0.817	0.847	0.880
TAR-SR	0.512	0.177	0.121	0.322	0.243	0.250	0.338	0.818	0.313	0.351	0.485	0.583	0.451	0.234	0.160		0.844	0.795	0.811	0.861
TAR-SRF	0.272	0.232	0.055	0.293	0.122	0.475	**0.035**	0.156	**0.012**	0.102	**0.000**	0.813	0.286	**0.001**	0.440	0.557		0.399	0.645	0.764
Logistic STAR-GARCH(1,1)	0.251	0.157	**0.049**	0.204	0.126	0.598	**0.043**	0.229	**0.004**	0.418	**0.027**	0.571	0.239	**0.023**	0.303	0.146	0.873		0.679	0.804
MS Two-state homoskedastic	0.111	0.145	0.058	0.193	0.172	0.280	0.149	0.074	0.051	0.152	0.139	0.491	0.111	0.055	0.148	0.105	0.246	0.707		0.735
MS Two-state heteroskedastic	0.343	**0.025**	**0.025**	**0.024**	**0.019**	0.381	0.120	0.212	0.078	0.383	0.111	0.273	0.361	0.093	0.485	0.292	0.750	0.410	0.813	

Panel J: Italian Stock Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponential STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.253	0.400	0.268	0.380	0.543	0.534	0.959	0.506	0.952	0.931	0.902	0.877	0.879	0.999	0.998	0.992	0.597	0.797	0.537
Random walk (with drift)	0.353		0.927	0.552	0.922	0.719	0.707	0.938	0.704	0.968	0.924	0.914	0.891	0.828	0.991	0.958	0.981	0.744	0.951	0.807
AR(1)	0.596	0.132		0.166	0.381	0.600	0.588	0.904	0.578	0.944	0.881	0.847	0.880	0.754	0.978	0.939	0.972	0.602	0.923	0.651
Random walk (with drift and GARCH(1,1))	0.897	0.769	0.434		0.893	0.730	0.711	0.948	0.698	0.978	0.936	0.912	0.891	0.823	0.986	0.952	0.978	0.730	0.945	0.799
AR(1) with GARCH(1,1)	0.975	0.230	1.000	0.219		0.624	0.610	0.923	0.598	0.960	0.902	0.859	0.882	0.765	0.974	0.939	0.970	0.621	0.932	0.685
GARCH(1,1) in mean and exogenous predictors	0.597	0.823	0.716	0.793	0.683		0.454	0.957	0.450	0.998	0.949	0.758	0.874	0.688	0.887	0.867	0.893	0.463	0.683	0.491
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.475	0.728	0.969	0.823	0.923	0.839		0.981	0.457	0.994	0.978	0.808	0.875	0.752	0.928	0.916	0.926	0.473	0.700	0.504
EGARCH(1,1)-in mean and exogenous predictors	0.220	0.472	0.488	0.060	0.390	0.282	0.120		**0.034**	0.817	0.446	0.315	0.811	0.158	0.538	0.463	0.500	**0.044**	0.311	0.107
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.270	0.925	0.921	0.947	0.991	0.917	0.957	0.152		0.976	0.953	0.890	0.880	0.842	0.972	0.982	0.968	0.507	0.742	0.526
TGARCH(1,1)-in mean and exogenous predictors	0.193	0.219	0.282	0.171	0.252	**0.003**	**0.011**	0.356	**0.028**		0.121	0.181	0.767	0.132	0.330	0.259	0.305	0.051	0.195	0.078
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.142	0.412	0.562	0.378	0.499	0.122	0.100	0.918	0.123	0.294		0.335	0.821	0.265	0.574	0.512	0.539	0.073	0.362	0.168
Exponential STAR - T-bill	0.351	0.090	0.116	0.186	0.345	0.740	0.750	0.782	**0.020**	0.580	0.619		0.846	0.395	0.733	0.674	0.709	0.104	0.464	0.191
Exponential STAR-SRF	0.460	0.159	0.212	0.261	0.321	0.450	0.478	0.444	0.488	0.425	0.633	0.563		0.160	0.202	0.183	0.180	0.123	0.163	0.135
Logistic STAR - T-bill	0.458	0.744	0.786	0.724	0.863	0.845	0.852	0.559	0.308	0.453	0.746	0.468	0.473		0.875	0.841	0.786	0.119	0.547	0.296
Logistic STAR-SRF	**0.006**	**0.017**	0.060	0.105	0.155	0.107	0.164	0.546	**0.037**	0.410	0.963	0.406	0.627	0.368		0.398	0.442	**0.001**	0.238	0.057
TAR-SR	**0.023**	0.327	0.441	0.300	0.404	0.449	0.486	0.772	**0.007**	0.419	0.979	0.860	0.735	0.637	0.567		0.540	**0.003**	0.298	0.106
TAR-SRF	**0.043**	0.076	0.076	0.170	0.186	0.074	**0.034**	0.327	0.116	0.549	0.678	0.649	0.605	0.658	0.533	0.944		**0.007**	0.273	0.082
Logistic STAR-GARCH(1,1)	0.939	0.383	0.669	0.903	0.985	0.593	0.455	0.224	0.250	0.197	0.131	0.364	0.460	0.414	**0.007**	**0.030**	**0.041**		0.783	0.528
MS Two-state homoskedastic	0.495	0.072	0.085	0.059	0.051	0.671	0.581	0.835	0.554	0.657	0.654	0.611	0.570	0.956	0.312	0.890	0.793	0.458		0.084
MS Two-state heteroskedastic	0.649	0.189	0.364	0.250	0.459	0.499	0.422	0.290	0.806	0.353	0.493	0.767	0.531	0.596	0.290	0.174	0.347	0.647	0.387	

Table 5

Diebold-Mariano and Giacomini-White Equal Predictive Accuracy Tests: Bond Return Forecasts

Panel A: United States Bond Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponentia l STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		**0.026**	**0.018**	**0.022**	**0.017**	0.364	0.566	0.540	0.852	0.678	0.758	0.956	0.775	0.984	**0.003**	0.999	0.948	0.868	**0.001**	**0.000**
Random walk (with drift)	0.096		0.417	0.568	0.515	0.984	0.986	0.988	0.994	0.991	0.991	0.997	0.995	0.993	0.851	0.998	0.996	0.995	**0.027**	**0.009**
AR(1)	0.160	0.322		0.611	0.667	0.991	0.992	0.992	0.998	0.995	0.995	0.999	0.997	0.995	0.879	0.999	0.997	0.997	**0.021**	**0.006**
Random walk (with drift and GARCH(1,1))	0.102	0.069	0.266		0.470	0.988	0.988	0.988	0.994	0.993	0.992	0.998	0.995	0.993	0.848	0.998	0.997	0.996	**0.013**	**0.003**
AR(1) with GARCH(1,1)	0.151	0.515	0.878	0.283		0.993	0.993	0.992	0.997	0.996	0.995	0.999	0.997	0.994	0.868	0.999	0.997	0.998	**0.009**	**0.002**
GARCH(1,1) in mean and exogenous predictors	0.708	0.113	0.106	0.106	0.084		0.875	0.643	0.936	0.882	0.912	0.979	0.848	0.983	**0.017**	0.996	0.963	0.907	**0.000**	**0.000**
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.915	0.090	0.091	0.094	0.072	0.353		0.493	0.901	0.649	0.853	0.971	0.803	0.982	**0.004**	0.991	0.950	0.880	**0.000**	**0.000**
EGARCH(1,1)-in mean and exogenous predictors	0.957	0.117	0.088	0.114	0.084	0.757	0.922		0.825	0.622	0.704	0.950	0.767	0.984	**0.010**	0.985	0.945	0.835	**0.001**	**0.000**
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.460	0.070	**0.032**	0.064	**0.027**	0.267	0.319	0.369		0.168	0.238	0.944	0.611	0.971	**0.002**	0.813	0.834	0.735	**0.000**	**0.000**
TGARCH(1,1)-in mean and exogenous predictors	0.741	0.071	0.073	0.066	0.059	0.483	0.952	0.836	0.470		0.661	0.960	0.759	0.980	**0.002**	0.986	0.934	0.849	**0.000**	**0.000**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.686	0.085	0.051	0.075	**0.038**	0.115	0.281	0.762	0.159	0.785		0.950	0.712	0.977	**0.002**	0.959	0.900	0.813	**0.000**	**0.000**
Exponential STAR - T-bill	0.275	**0.042**	**0.023**	**0.038**	**0.020**	0.161	0.203	0.297	0.252	0.247	0.319		0.051	0.852	**0.004**	0.197	0.228	0.184	**0.000**	**0.000**
Exponential STAR-SRF	0.636	0.068	**0.010**	0.067	**0.006**	0.609	0.691	0.788	0.318	0.809	0.778	0.109		0.949	**0.021**	0.607	0.696	0.617	**0.000**	**0.000**
Logistic STAR - T-bill	0.123	0.062	**0.048**	0.061	**0.047**	0.111	0.114	0.118	0.176	0.129	0.144	0.377	0.198		**0.005**	0.052	0.059	0.072	**0.002**	**0.001**
Logistic STAR-SRF	**0.045**	0.345	0.533	0.388	0.558	0.143	**0.044**	0.120	**0.028**	**0.022**	**0.018**	0.057	0.122	0.051		1.000	0.998	0.998	**0.009**	**0.005**
TAR-SR	**0.021**	**0.029**	**0.029**	**0.026**	**0.026**	**0.035**	0.068	**0.030**	0.729	0.112	0.207	0.706	0.955	0.263	**0.003**		0.610	0.522	**0.000**	**0.000**
TAR-SRF	0.291	0.052	**0.034**	**0.046**	**0.031**	0.243	0.315	0.309	0.694	0.352	0.520	0.599	0.808	0.218	**0.032**	0.876		0.442	**0.000**	**0.000**
Logistic STAR-GARCH(1,1)	0.376	**0.048**	**0.018**	**0.031**	**0.010**	0.326	0.420	0.574	0.796	0.532	0.640	0.645	0.916	0.365	**0.026**	0.595	0.910		**0.000**	**0.000**
MS Two-state homoskedastic	**0.019**	0.170	0.091	0.103	**0.042**	**0.009**	**0.009**	**0.012**	**0.008**	**0.007**	**0.006**	**0.009**	**0.003**	**0.019**	0.084	**0.003**	**0.002**	**0.000**		**0.043**
MS Two-state heteroskedastic	**0.013**	0.060	**0.042**	**0.041**	**0.017**	**0.006**	**0.006**	**0.007**	**0.005**	**0.005**	**0.004**	**0.007**	**0.001**	**0.014**	0.052	**0.002**	**0.001**	**0.000**	0.214	

Panel B: United Kingdom Bond Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponentia l STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
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)	0.768		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)	0.317	0.444		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))	0.764	1.000	0.231		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)	0.474	0.634	**0.040**	0.304		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	0.815	0.794	0.563	0.776	0.693		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.	0.341	0.802	0.452	0.772	0.584	0.755		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	0.383	0.670	0.700	0.607	0.745	0.442	0.121		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.	0.621	0.778	0.735	0.736	0.826	0.822	0.992	0.419		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	0.800	0.822	0.684	0.814	0.789	0.504	0.310	0.326	0.856		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.	0.387	0.871	0.655	0.859	0.794	0.552	0.922	0.440	0.853	0.464		0.963	0.989	0.828	0.989	0.908	0.804	0.933	**0.000**	**0.000**
Exponential STAR - T-bill	0.194	0.124	0.154	0.118	0.132	0.173	0.141	0.147	0.166	0.169	0.133		0.069	0.081	0.069	0.101	0.094	0.055	**0.000**	**0.000**
Exponential STAR-SRF	0.674	0.646	0.351	0.634	0.438	0.288	0.203	0.112	0.266	0.182	0.088	0.266		0.531	0.328	0.711	0.528	0.052	**0.000**	**0.000**
Logistic STAR - T-bill	0.780	0.685	0.555	0.689	0.584	0.474	0.364	0.579	0.459	0.673	0.550	0.366	0.785		0.469	0.666	0.502	0.297	**0.000**	**0.000**
Logistic STAR-SRF	0.674	0.646	0.351	0.634	0.438	0.288	0.203	0.112	0.266	0.182	0.088	0.266	0*	0.785		0.711	0.528	0.052	**0.000**	**0.000**
TAR-SR	0.448	0.463	0.092	0.429	0.104	0.183	0.277	0.240	0.320	0.186	0.228	0.396	0.583	0.515	0.583		0.370	0.164	**0.000**	**0.000**
TAR-SRF	0.678	0.603	0.645	0.594	0.663	0.840	0.750	0.646	0.774	0.845	0.660	0.405	0.706	0.873	0.706	0.590		0.338	**0.000**	**0.000**
Logistic STAR-GARCH(1,1)	0.942	0.676	0.418	0.656	0.504	0.243	0.416	0.154	0.581	0.145	0.203	0.232	0.341	0.701	0.341	0.370	0.890		**0.000**	**0.000**
MS Two-state homoskedastic	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.001**	**0.000**	**0.000**	**0.001**	**0.000**		0.705
MS Two-state heteroskedastic	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.003**	**0.000**	**0.001**	**0.000**	**0.001**	**0.001**	**0.000**	0.644	

Table 5 [Cont.]

Diebold-Mariano and Giacomini-White Equal Predictive Accuracy Tests: Bond Return Forecasts

Panel C: Japanese Bond Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponentia l STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.083	0.085	0.072	0.076	0.591	0.585	0.507	0.514	0.636	0.620	0.929	0.406	0.548	0.982	0.951	0.848	**0.040**	0.950	0.897
Random walk (with drift)	0.393		0.834	0.388	0.474	0.946	0.973	0.954	0.966	0.950	0.977	0.966	0.922	0.954	0.991	0.988	0.979	0.876	0.986	0.992
AR(1)	0.393	0.531		0.252	0.347	0.947	0.974	0.954	0.967	0.951	0.978	0.965	0.913	0.949	0.992	0.988	0.980	0.869	0.987	0.993
Random walk (with drift and GARCH(1,1))	0.357	0.775	0.716		0.743	0.954	0.977	0.962	0.972	0.957	0.981	0.969	0.929	0.942	0.993	0.991	0.983	0.895	0.989	0.995
AR(1) with GARCH(1,1)	0.358	0.323	0.326	0.784		0.948	0.974	0.957	0.968	0.952	0.977	0.968	0.926	0.937	0.993	0.990	0.980	0.888	0.989	0.994
GARCH(1,1) in mean and exogenous predictors	0.811	0.320	0.320	0.286	0.306		0.512	0.320	0.365	0.995	0.585	0.899	0.366	0.511	0.969	0.892	0.848	0.086	0.944	0.879
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.847	0.161	0.157	0.135	0.161	0.609		0.335	0.133	0.569	0.988	0.889	0.355	0.509	0.956	0.875	0.827	0.064	0.940	0.884
EGARCH(1,1)-in mean and exogenous predictors	0.553	0.286	0.289	0.246	0.274	0.208	0.563		0.518	0.757	0.734	0.909	0.392	0.552	0.966	0.912	0.886	0.081	0.941	0.884
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.742	0.212	0.212	0.180	0.207	0.662	0.319	0.368		0.705	0.958	0.902	0.392	0.550	0.964	0.901	0.876	0.070	0.945	0.897
TGARCH(1,1)-in mean and exogenous predictors	0.791	0.304	0.303	0.271	0.291	**0.031**	0.620	0.299	0.637		0.503	0.895	0.344	0.491	0.966	0.881	0.816	0.070	0.940	0.868
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.823	0.139	0.136	0.118	0.141	0.486	0.086	0.435	0.159	0.515		0.885	0.332	0.489	0.953	0.867	0.801	**0.049**	0.936	0.873
Exponential STAR - T-bill	0.113	0.107	0.112	0.093	0.093	0.226	0.352	0.225	0.294	0.237	0.370		0.079	0.128	0.364	0.203	0.147	**0.045**	0.482	0.249
Exponential STAR-SRF	0.895	0.417	0.465	0.417	0.425	0.944	0.603	0.859	0.939	0.926	0.813	0.346		0.673	0.959	0.938	0.825	0.264	0.917	0.849
Logistic STAR - T-bill	1.000	**0.036**	**0.031**	**0.040**	**0.048**	**0.000**	**0.000**	**0.016**	**0.001**	**0.000**	**0.000**	0.470	0.177		0.858	0.825	0.669	0.239	0.850	0.744
Logistic STAR-SRF	0.130	0.086	0.084	0.072	0.076	0.204	0.263	0.218	0.228	0.218	0.276	0.915	0.246	0.554		0.168	0.092	**0.009**	0.605	0.231
TAR-SR	0.274	0.095	0.098	0.077	0.078	0.802	0.417	**0.021**	0.177	0.768	0.420	0.555	0.277	0.617	0.616		0.217	**0.013**	0.748	0.438
TAR-SRF	0.297	0.188	0.188	0.168	0.183	0.299	0.287	0.246	0.231	0.367	0.324	0.435	0.500	0.240	0.371	1.000		**0.024**	0.873	0.705
Logistic STAR-GARCH(1,1)	0.258	0.524	0.543	0.505	0.512	0.215	0.340	0.118	0.370	0.211	0.277	0.090	0.643	**0.000**	0.061	0.112	0.177		0.975	0.973
MS Two-state homoskedastic	0.246	0.065	0.066	0.050	0.052	0.265	0.293	0.290	0.279	0.275	0.306	0.327	0.380	0.234	0.720	0.448	0.426	0.149		0.060
MS Two-state heteroskedastic	0.395	**0.025**	**0.025**	**0.016**	**0.016**	0.421	0.398	0.436	0.366	0.438	0.424	0.751	0.541	0.762	0.582	0.989	0.718	0.138	0.311	

Panel D: German Bond Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponentia l STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.256	0.083	0.294	0.092	0.925	0.937	0.963	0.841	0.841	0.732	0.254	0.851	0.800	0.138	0.993	0.950	**0.017**	0.957	0.819
Random walk (with drift)	0.586		0.287	0.877	0.323	0.879	0.877	0.917	0.825	0.838	0.795	0.639	0.758	0.820	0.744	0.964	0.986	0.398	0.974	0.905
AR(1)	0.425	0.767		0.754	0.623	0.960	0.961	0.987	0.947	0.942	0.924	0.797	0.925	0.918	0.917	0.992	0.989	0.572	0.986	0.967
Random walk (with drift and GARCH(1,1))	0.556	0.326	0.662		0.280	0.853	0.850	0.897	0.797	0.809	0.761	0.601	0.721	0.788	0.706	0.957	0.985	0.363	0.969	0.886
AR(1) with GARCH(1,1)	0.452	0.627	0.755	0.575		0.957	0.955	0.989	0.949	0.940	0.916	0.784	0.917	0.912	0.908	0.992	0.988	0.543	0.985	0.961
GARCH(1,1) in mean and exogenous predictors	0.244	0.157	0.261	0.161	0.266		0.248	0.774	0.300	0.108	**0.023**	**0.046**	0.092	0.108	0.074	0.903	0.855	**0.010**	0.877	0.571
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.188	0.252	0.248	0.244	0.255	0.801		0.822	0.410	0.455	0.055	**0.046**	0.090	0.230	0.063	0.939	0.888	**0.010**	0.906	0.633
EGARCH(1,1)-in mean and exogenous predictors	0.187	0.076	0.110	0.080	0.101	0.496	0.387		0.071	0.095	**0.040**	**0.030**	**0.045**	0.121	**0.037**	0.815	0.806	**0.001**	0.821	0.446
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.373	0.224	0.301	0.229	0.296	0.745	0.996	0.324		0.558	0.336	0.113	0.190	0.436	0.158	0.960	0.906	**0.005**	0.895	0.652
TGARCH(1,1)-in mean and exogenous predictors	0.420	0.215	0.344	0.218	0.356	0.379	0.967	0.299	0.856		0.132	0.101	0.186	0.307	0.159	0.926	0.874	**0.020**	0.899	0.638
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.806	0.355	0.390	0.342	0.438	0.146	0.192	0.181	0.828	0.363		0.164	0.320	0.636	0.268	0.964	0.913	**0.030**	0.939	0.746
Exponential STAR - T-bill	0.431	0.917	0.594	0.899	0.661	0.228	0.176	0.174	0.451	0.463	0.578		0.786	0.884	0.746	0.997	0.970	0.148	0.968	0.867
Exponential STAR-SRF	0.291	0.560	0.397	0.532	0.416	0.296	0.269	0.228	0.472	0.506	0.923	0.636		0.760	0.146	0.991	0.945	**0.015**	0.954	0.807
Logistic STAR - T-bill	0.307	0.359	0.428	0.347	0.429	0.297	0.735	0.373	0.957	0.809	0.915	0.076	0.358		0.199	0.961	0.901	**0.040**	0.928	0.702
Logistic STAR-SRF	0.328	0.586	0.426	0.556	0.453	0.244	0.188	0.187	0.373	0.420	0.805	0.420	0.288	0.307		0.993	0.950	**0.018**	0.957	0.820
TAR-SR	0.078	0.233	0.054	0.269	0.054	0.454	0.329	0.456	0.261	0.359	0.225	**0.032**	0.092	0.246	0.078		0.678	**0.000**	0.612	0.241
TAR-SRF	0.183	0.063	**0.040**	0.068	**0.036**	0.542	0.434	0.685	0.326	0.492	0.355	0.087	0.210	0.400	0.182	0.781		**0.012**	0.482	0.191
Logistic STAR-GARCH(1,1)	**0.010**	0.859	0.984	0.797	0.953	**0.011**	**0.004**	**0.001**	**0.002**	**0.011**	**0.008**	0.369	**0.004**	**0.002**	**0.010**	**0.008**	**0.024**		0.981	0.944
MS Two-state homoskedastic	0.147	0.114	0.116	0.103	0.127	0.170	0.151	0.145	0.157	0.167	0.125	0.100	0.151	0.143	0.147	0.764	0.875	0.113		**0.011**
MS Two-state heteroskedastic	0.094	0.206	0.072	0.174	0.067	0.157	0.170	0.070	0.127	0.117	0.125	**0.047**	0.098	0.124	0.094	0.501	0.476	**0.046**	**0.036**	

Table 5 [Cont.]

Diebold-Mariano and Giacomini-White Equal Predictive Accuracy Tests: Bond Return Forecasts

Panel E: French Bond Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponentia l STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.115	0.109	0.050	0.059	0.248	0.070	0.115	0.674	0.759	0.614	0.852	0.083	0.581	0.802	0.989	0.626	0.845	0.856	0.792
Random walk (with drift)	0.501		0.538	0.093	0.255	0.856	0.737	0.760	0.948	0.904	0.908	0.939	0.799	0.885	0.965	0.981	0.889	0.885	0.971	0.980
AR(1)	0.381	0.857		0.080	**0.038**	0.862	0.745	0.760	0.953	0.907	0.907	0.946	0.812	0.891	0.955	0.988	0.885	0.891	0.983	0.988
Random walk (with drift and GARCH(1,1))	0.192	0.347	0.268		0.722	0.934	0.865	0.875	0.977	0.954	0.953	0.969	0.903	0.950	0.986	0.994	0.950	0.950	0.988	0.993
AR(1) with GARCH(1,1)	0.209	0.687	0.101	0.639		0.924	0.841	0.854	0.974	0.946	0.944	0.965	0.889	0.941	0.978	0.994	0.936	0.941	0.989	0.994
GARCH(1,1) in mean and exogenous predictors	0.298	0.573	0.452	0.259	0.271		0.130	0.188	0.740	0.830	0.681	0.859	0.224	0.752	0.845	0.986	0.711	0.752	0.873	0.826
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.157	0.723	0.779	0.589	0.609	0.243		0.559	0.946	0.895	0.866	0.937	0.761	0.930	0.910	0.994	0.863	0.930	0.951	0.924
EGARCH(1,1)-in mean and exogenous predictors	0.362	0.748	0.729	0.418	0.461	0.413	0.825		0.920	0.982	0.925	0.901	0.604	0.885	0.914	0.992	0.869	0.885	0.917	0.903
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.812	0.308	0.214	0.109	0.106	0.870	0.233	0.454		0.574	0.448	0.777	0.105	0.326	0.700	0.886	0.474	0.326	0.819	0.757
TGARCH(1,1)-in mean and exogenous predictors	0.323	0.412	0.342	0.149	0.185	0.629	0.350	0.116	0.553		0.356	0.709	0.125	0.241	0.665	0.820	0.402	0.241	0.746	0.679
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.644	0.431	0.405	0.175	0.245	0.828	0.502	0.437	0.092	0.808		0.775	0.191	0.386	0.707	0.869	0.502	0.386	0.799	0.742
Exponential STAR - T-bill	0.329	0.306	0.272	0.214	0.146	0.416	0.153	0.503	0.658	0.899	0.708		0.084	0.148	0.444	0.479	0.235	0.148	0.575	0.490
Exponential STAR-SRF	0.343	0.614	0.510	0.341	0.295	0.784	0.261	0.541	0.348	0.535	0.259	0.199		0.917	0.891	0.997	0.837	0.917	0.931	0.892
Logistic STAR - T-bill	0.118	0.501	0.381	0.192	0.209	0.298	0.157	0.362	0.812	0.323	0.644	0.329	0.343		0.802	0.989	0.626	0.844	0.856	0.792
Logistic STAR-SRF	0.664	0.191	0.204	0.070	0.105	0.532	0.342	0.399	0.784	0.882	0.707	0.484	0.490	0.664		0.562	0.227	0.198	0.634	0.548
TAR-SR	0.130	0.147	0.062	**0.039**	**0.034**	0.147	0.060	0.102	0.323	0.140	0.115	0.144	**0.047**	0.130	0.997		0.107	**0.011**	0.611	0.501
TAR-SRF	0.682	0.497	0.477	0.233	0.291	0.871	0.491	0.587	0.842	0.756	0.740	0.800	0.697	0.682	0.675	0.149		0.374	0.808	0.732
Logistic STAR-GARCH(1,1)	0.124	0.501	0.381	0.192	0.209	0.298	0.157	0.362	0.812	0.323	0.644	0.329	0.343	0.228	0.664	0.130	0.682		0.856	0.792
MS Two-state homoskedastic	0.237	**0.032**	0.107	**0.039**	0.078	0.267	**0.049**	0.296	0.174	0.744	0.499	0.951	0.056	0.237	0.939	0.213	0.586	0.237		0.299
MS Two-state heteroskedastic	0.677	0.061	0.070	0.051	**0.022**	0.583	0.289	0.417	0.686	0.868	0.663	0.471	0.467	0.677	0.767	0.970	0.624	0.677	0.844	

Panel F: Canadian Bond Returns, 1-month Horizon

	Linear	Random walk (with drift)	AR(1)	Random walk (with drift and GARCH(1,1))	AR(1) with GARCH(1,1)	GARCH(1,1) in mean and exogenous predictors	GARCH(1,1)-in mean and exogenous predictors - t dist.	EGARCH(1,1)-in mean and exogenous predictors	EGARCH(1,1)-in mean and exogenous predictors- t dist.	TGARCH(1,1)-in mean and exogenous predictors	TGARCH(1,1)-in mean and exogenous predictors- t dist.	Exponential STAR-T-bill	Exponentia l STAR-SRF	Logistic STAR-T-bill	Logistic STAR-SRF	TAR-SR	TAR-SRF	Logistic STAR-GARCH(1,1)	MS Two-state homoskedastic	MS Two-state heteroskedastic
Linear		0.059	0.062	**0.038**	**0.043**	0.054	0.134	0.159	0.136	0.398	0.106	0.637	0.936	0.386	**0.006**	0.229	0.807	**0.035**	0.866	0.840
Random walk (with drift)	0.269		0.702	0.378	0.489	0.845	0.892	0.911	0.923	0.941	0.920	0.982	0.994	0.934	0.579	0.860	0.984	0.586	0.998	0.997
AR(1)	0.270	0.281		0.309	0.407	0.826	0.879	0.903	0.915	0.935	0.915	0.982	0.994	0.931	0.553	0.857	0.984	0.559	0.998	0.997
Random walk (with drift and GARCH(1,1))	0.197	0.930	0.492		0.784	0.910	0.925	0.952	0.950	0.964	0.947	0.989	0.996	0.961	0.632	0.890	0.991	0.641	0.999	0.999
AR(1) with GARCH(1,1)	0.202	0.596	0.649	0.281		0.877	0.905	0.938	0.937	0.956	0.938	0.989	0.997	0.956	0.589	0.883	0.990	0.593	0.999	0.999
GARCH(1,1) in mean and exogenous predictors	0.190	0.400	0.636	0.305	0.452		0.904	0.911	0.932	0.970	0.932	0.943	0.985	0.940	0.112	0.731	0.987	0.053	0.985	0.980
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.276	0.483	0.474	0.385	0.351	0.473		0.530	0.753	0.910	0.795	0.818	0.956	0.769	**0.029**	0.537	0.960	**0.035**	0.940	0.929
EGARCH(1,1)-in mean and exogenous predictors	0.564	0.284	0.345	0.203	0.264	0.127	0.687		0.654	0.858	0.742	0.824	0.967	0.740	**0.034**	0.526	0.939	**0.042**	0.951	0.943
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.200	0.378	0.373	0.269	0.293	0.340	0.529	0.943		0.891	0.712	0.790	0.959	0.703	**0.011**	0.458	0.949	**0.035**	0.935	0.922
TGARCH(1,1)-in mean and exogenous predictors	0.957	0.285	0.300	0.192	0.220	0.130	0.222	0.444	0.215		0.212	0.668	0.916	0.450	**0.011**	0.304	0.843	**0.018**	0.870	0.848
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.408	0.344	0.358	0.251	0.272	0.176	0.306	0.787	0.164	0.382		0.748	0.949	0.583	**0.012**	0.374	0.902	**0.038**	0.913	0.896
Exponential STAR - T-bill	0.732	0.056	0.053	**0.031**	**0.031**	0.205	0.112	0.442	0.201	0.489	0.443		0.826	0.250	**0.007**	0.166	0.627	**0.025**	0.790	0.747
Exponential STAR-SRF	0.089	**0.014**	**0.017**	**0.006**	**0.011**	**0.035**	**0.018**	**0.046**	0.077	0.179	0.089	0.198		0.059	**0.002**	**0.028**	0.258	**0.014**	0.402	0.370
Logistic STAR - T-bill	0.241	0.237	0.237	0.158	0.170	0.172	0.374	0.489	0.510	0.548	0.508	0.394	0.053		**0.018**	0.317	0.799	**0.048**	0.903	0.878
Logistic STAR-SRF	0.060	0.584	0.768	0.724	0.783	0.180	0.240	0.217	0.114	0.092	0.102	0.056	**0.003**	0.093		0.929	0.998	0.509	0.999	0.998
TAR-SR	0.391	0.100	0.113	0.102	0.130	0.247	0.469	0.487	0.610	0.588	0.594	0.577	**0.029**	0.428	0.104		0.886	0.169	0.929	0.912
TAR-SRF	0.820	0.114	0.108	0.072	0.070	0.056	0.121	0.335	0.129	0.156	0.341	0.926	0.283	0.516	**0.030**	0.220		**0.007**	0.660	0.621
Logistic STAR-GARCH(1,1)	0.216	0.933	0.696	0.866	0.718	0.113	0.249	0.199	0.234	0.134	0.234	0.140	**0.006**	0.169	0.989	0.284	0.062		0.993	0.991
MS Two-state homoskedastic	0.334	**0.025**	**0.021**	**0.012**	**0.010**	**0.049**	0.198	0.139	0.163	0.438	0.260	0.742	0.960	**0.015**	**0.009**	0.100	0.346	0.056		0.235
MS Two-state heteroskedastic	0.407	**0.038**	**0.033**	**0.020**	**0.017**	0.065	0.222	0.167	0.198	0.492	0.322	0.859	0.928	**0.028**	**0.018**	0.159	0.442	0.072	0.624	