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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 linear and non-linear models for stock and bond returns in the G7 countries. Besides Markov switching, threshold autoregressive (TAR), and smooth transition autoregressive (STAR) regime switching models, we also estimate univariate models in which conditional heteroskedasticity is captured by a GARCH and in which predicted volatilities appear in the conditional mean function. Although we fail to find a consistent winner/out-performer across all countries and markets, it turns out that capturing non-linear effects may be key to improve forecasting. U.S. and U.K. asset return data are "special" in the sense that good predictive performance seems to require that non-linear dynamics be modeled, especially using a Markov switching framework. Although occasionally stock and bond return forecasts for other G7 countries also appear to benefit from non-linear modeling (especially of TAR and STAR type), data from France, Germany, and Italy imply that the best predictive model is often one of the simple benchmarks, such as the random walk and univariate auto-regressions. U.S. and U.K. markets also provide the only data for which we find statistically significant differences between forecasting models. Results appear to be remarkably stable over time, robust to changes in the loss function used in statistical evaluations as well as to the methodology employed to perform pair-wise comparisons.

Keywords: Non-linearities, regime switching, threshold predictive regressions, forecasting.
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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 since the late 1970s. Against the background

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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 (e.g., in portfolio choice applications) prediction variables, see e.g., Rapach, Wohar, and Rangvid (2005). On the other hand, much interest has concerned the possibility that – even conditioning on the use of rather traditional and unsophisticated sets of variables (such as those explored 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 rates and bond returns dynamics, for which major examples include Balke and Fomby (1997), Enders and Granger (1998), Franses and van Dijk (2000), Guidolin and Timmermann (2008), Lekkos and Milas (2004), and McMillan (2004); equity returns, see e.g., Martens, Kofman and Vorst (1998), Guidolin and Timmermann (2006), Leung, Daouk and Chen (2000), McMillan (2001, 2003), 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 may be beneficial in forecasting applications. 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 (see van Dijk and Franses, 2003), and that non-linear models could be in some sense providing useful approximations and yet be "wrong", i.e. they might be sample-specific and unable to capture the presence of time variations in non-linear dynamics (see e.g., Clements and Smith, 1999). Nevertheless, a true test of the usefulness of a model in describing data, and therefore in informing market agents or policy makers, must be its ability to forecast. Clements, Franses, and Swanson (2004) evaluate these arguments against and in favor of using non-linear models in applied economics and conclude that, even though the evidence in favor of constructing forecasts using non-linear models is rather sparse, there is reason to be optimistic.

The objective of our paper is to perform a systematic evaluation of whether, when, and where non-linear econometric models may provide accurate forecasts of financial returns. We do this by forecasting monthly stock and bond returns in the G7 countries and using – against a baseline linear framework characterized by the absence of any non-linear structure – a standard set of macroeconomic variables widely used in the empirical finance literature (changes in short-term interest rates, the term spread, the dividend yield, the inflation rate, the 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 vs. the U.S. dollar). Since our goal does

[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).

not consist in showing that any peculiar kind of non-linear econometric framework is optimal, in this paper we consider a wide range of prediction models, including standard Markov switching predictive regressions, threshold predictive regressions, and 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 linear regression), such as the random walk model with drift and a univariate autoregression.

Besides returning to the key question of whether non-linear models may improve realized 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 and the conditional heteroskedastic function often discussed by volatility researchers, thus creating a mean-variance/CAPM-style connection between level forecasts and volatility predictions. Therefore we contrast ARCH-in mean predictive regression models obtained under a number of alternative assumptions on the detailed structure of the ARCH model and on the marginal distribution of the shocks with both simpler benchmarks and with proper non-linear models.

We find three important results. First, U.S. and U.K. return data appear to be "special" in the sense that good predictive performance demands for the estimation of non-linear models, especially (but not exclusively) of the Markov switching type. Although occasionally stock and bond returns from other G7 countries also appear to require exploiting non-linearities to successfully predict their subsequent dynamics (especially threshold autoregressive, TAR, and smooth transition autoregressive, STAR, models), data from France, Germany, and Italy mostly yield interesting predictive results on the basis of simpler benchmarks, including a naive linear homoskedastic model. This is consistent with the conclusion of Clements, Franses, and Swanson (2004) that applied non-linear forecasting methods are not simply "hopeless", although the evidence in their favor is usually scattered. However, where our results contribute to the debate is by isolating a subset of markets – essentially, U.S. and U.K. equity and bond markets – in which non-linear model appear to consistently out-perform all other models that we, as designers of the forecasting experiments, have "thrown at them".

Second, U.S. and U.K. data appear to be special in another sense: these are the only two countries in which data are rich enough to allow us to find statistically significant differences in the recursive out-of-sample performance of different models. This is done using a variety of methods, from Diebold and Mariano (1995)-type tests (including McCracken's (2007) nested models adjustments), to more sophisticated van Dijk and Franses (2003) tests that overweight the importance of accurately predicting the tails, to the new conditional testing framework proposed by Giacomini and White (2006). For most of these tests, we find that many non-linear models – among them Markov switching predicting regressions – outperform most other models in pseudo-out-of-sample experiments. Third, we report evidence consistent with a claim that the good forecasting performance of (some) non-linear models would not entirely derive from "lucky" sample periods in which the right kind of non-linear dynamics has manifested itself in a sufficiently persistent way. Although a few interesting patterns can be found, it does not seem that a role for non-linear models depends on any particular part of our sample; to be more precise, the good forecasting performance depends on portions of our overall sample that are specific to each country under examination, which shows that there is no structure in the patterns one may be looking for to justify ex-post why non-linear models may prove useful in financial applications.[2]

Many papers are related to our research design.[3] At least three come to mind (but see also the papers cited earlier in this Introduction). Teräsvirta, van Dijk, and Medeiros (2005) systematically examine the predictive accuracy of linear autoregressive, STAR, and neural network models for 47 monthly macroeconomic variables in the G7 economies. They report encouraging results for the non-linear camp (in particular, from STAR models), although they also stress that careful specification of non-linear time series models is of crucial importance to generate accurate predictions. Although there are differences in the class of models we experiment with, one can view our paper as an extension of Teräsvirta, van Dijk, and Medeiros's efforts from macroeconomic applications to modeling and predicting equity and bond returns in the G7 countries. Rapach, Wohar, and Rangvid (2005) report results for another large-scale, forecasting simulation experiment targeting financial returns. They examine the predictability of stock returns using macroeconomic variables in 12 industrialized countries. They use linear prediction models, although their structure is based on a painstaking effort that analyzes the predictive ability of each macro variable in turn and employs a procedure that combines general-to-specific model selection with out-of-sample tests of forecasting ability in an effort to identify the best model in each country. Rapach et al (2005). conclude that interest rates are the most consistent and reliable predictors of stock returns. Differently from Rapach, Wohar, and Rangvid's paper, we also examine the predictability of long-term bond returns and take a distinct interest in the (pseudo-) out-of-sample performance of a variety of non-linear models. Sarantis (2001) employs STAR models to investigate the 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, while out-of-sample forecasts from the models outperform a random walk. In a way, we are extending Sarantis' research design to include bond returns among the target forecast variables and we are enlarging the class of non-linear models well beyond STAR models.[4]

The paper is structured as follows. Section 2 describes the data. Section 3 introduces a range of econometric frameworks, including a number of non-linear models. Section 4 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 statistical evidence of over-performance of any model when compared with its competitors. Section 5 presents the results, distinguishing between the general implications of our massive forecasting experiments and country- and asset-specific results of relevance in applied terms. Section 6 presents a few additional empirical results as a way of performing robustness checks. Section 7 concludes.

[2] However, for at least five out of seven of the countries examined, we have uncovered that the more turbulent 1999-2002 period implies a lower amount of predictability (e.g., in terms of mean squared forecast error and of the ability to correctly forecast the sign of returns) than the remaining periods, even though in this stretch of time non-linear models perform as well as (better, as poorly as) most other models.

[3] There are hundreds of published papers on modeling non-linear patterns in individual financial time series and on interpreting the economic meanings of such patterns. We have no presumption of being exhaustive in citing and reviewing this literature. See Clements, Franses, and Swanson (2004) and Franses and van Dijk (2000) for general references.

[4] A few other papers deserve mention, although they simply consist of applications of non-linear modeling to specific countries and markets. For U.S. data, McMillan (2001) finds evidence 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) use STR models to 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).

One appendix provides details on the data used in the paper, their construction, and the original data sources.

2. Data

We use monthly data on asset returns and a standard set of predictive variables sampled over the period 1979:02 - 2007:01. The data are obtained from Datastream and Global Financial Database and they concern financial returns and macroeconomic variables for the G7 countries. The series we collect are stock (r_t^{stock}) and bond (r_t^{bond}) returns, the log-dividend yield on equities (dy_t), changes in the short-term interest rate (3-month Treasury bill yields, Δi_t), the term spread ($Term_t$) defined as the difference between long- (10 year) and the short-term (3-month bill) government bond yields, the change in the effective log-exchange rate (Δs_t), the CPI inflation rate (π_t), changes in log-oil prices (Δoil_t), industrial production growth (ΔIP_t), and the change in the unemployment rate (Δu_t). Inflation, industrial production growth and the unemployment rates are seasonally adjusted. An Appendix in Guidolin et al. (2008) gives details on the data sources and the series 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 Japan 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 in the literature, i.e., on average returns of 13-14% per year vs. annualized volatilities of 14-16%. A less well-known feature of the financial data is that in the G7, between 1979 and 2007, realized bond returns tend to yield an average comparable to stock returns and yet display considerably lower volatility. 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. 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 signalled by the Jarque-Bera's test. In particular, stock returns systematically display negative skewness (Italy is the only exception) and high kurtosis. The features are similar for bond returns, although now 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 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 for the U.K. represents an exception) and ranges from 64 basis points (b.p.) in the U.K. to 2046 b.p. in the U.S. The CPI inflation rate corresponds to the 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.

3. The Forecasting Models

Although most the econometric models employed in this paper to forecast asset returns have already been largely investigated (usually on a one-by-one basis) in the literature, it is useful to briefly but systematically 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" and provide details on the specific versions that we have actually employed in the paper.

3.1. *Linear Models*

Our baseline forecasting model is represented by a simple linear regression framework that projects asset returns at time $t+h$ $(h \geq 1)$ on the macroeconomic variables that belong to the time t information set $(\mathcal{I}_t)$:

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

where j equals either s (stocks) or b (bonds), $\mathbf{X}_t \equiv [r^j_t \; dy_t \; \Delta i_t \; TERM_t \; \Delta s_t \; \Delta oil_t \; \pi_t \; \Delta ip_t \; \Delta u_t]'$, and ϵ^j_{t+h} is a martingale difference sequence. Also, let m be the number of variables collected by $\mathbf{X}_t$, i.e. the number of columns of this $T \times m$ matrix (T is the total sample size). Notice that from (1) we have omitted a subscript or superscript to denote the country/markets under investigation, to simplify our notation. However, the unknown parameters α^j_h and $\boldsymbol{\beta}^j_h$ 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. Linear models such as (1) have received tremendous attention in the literature, see Guidolin and Ono (2006) and Rapach, Wohar, and Rangvid (2005) and references therein.

The prediction variables are selected "on the shoulders" of vast literature started by Chen, Roll and Ross (1986) who have systematically investigated the linkages between stock returns and inflation, money growth, and a wide of macroeconomic variables, identifying the importance of the term spread, oil prices and industrial production growth in explaining stock return behavior. Among many others, Cutler, Poterba and Summers (1989) have provided specific 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 reported by Fama and French (1989) while interest rates have been also commonly adopted as predictor variables (see Ang and Bekaert, 2007). Boyd, Hu and Jagannathan (2005) demonstrate the ability of the unemployment rate to predict stock returns. This evidence has been generalized to a number of countries that belong to our G7 sample. Asprem (1989) documents a positive relationship between stock returns and real activity using data from 10 European countries in addition to finding support for the forecasting power of money supply, interest rate and exchange rate variables. The strength of the relation between stock returns and real activity (industrial production) is further enhanced by the findings of Fama (1990). Additionally, Cheung and Ng (1998) provide evidence of long-run relationships between the stock market and the macro economy for five stock markets (the U.S., Canada, Germany, Italy and Japan). These long run relationships provide additional explanatory power for stock returns to that contained in dividend yields, default and term spreads.

3.2. *ARCH-in Mean Models*

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

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

where $\hat{\sigma}^j_{t+h}$ is a prediction at time t of the volatility of the return of asset j at time $t+h$. For instance, the simplest case is when the conditional heteroskedasticity model is 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 the standard residual $\eta^j_t \equiv \epsilon^j_t/\sqrt{h^j_t}$ is standard normal, and $\hat{\sigma}^j_{t+1} = \sqrt{\hat{\omega}^j + \hat{\zeta}^j(\eta^j_t)^2 + \hat{\theta}^j h^j_t}$.[5] Notice that this framework projects 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,

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

where $F(0, h^j_{t+h}; \boldsymbol{\nu})$ is a specified parametric distribution function (with parameters $\boldsymbol{\nu}$). 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 is 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 denoting 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 denoting 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.

3.3. *Markov Switching Models*

The popular press often acknowledges the existence of financial market states by referring to them as "bull" and "bear" markets, see Guidolin and Timmermann (2005). 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:

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

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

where the constant α^j_{h,S_t}, the regression coefficients in $\boldsymbol{\beta}^j_{h,S_t}$, and the variance h^j_{t+h,S_t} all depend on an *unobservable* state variable S^j_t, an indicator variable taking values $1, 2, ...k$, where k is the number of states. 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 econometrician using the history of asset returns. Similarly to a growing literature on switching models in finance (see e.g. Guidolin and Timmermann, 2006), we assume that S^j_t 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^j_{il} defined as

$$\Pr(S^j_{t+1} = l | S^j_t = i) = p^j_{il}, \quad i, l = 1, .., k, \tag{5}$$

i.e., the probability of switching to state l between t and $t+1$ given that at time t the market is in state i. 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, in this paper we impose and estimate simple two-state predictive regressions in which $k = 2$.[6] As a result (4) can be re-written as:

$$r^j_{t+h} = [I^j_t \alpha^j_{h,1} + (1 - I^j_t)\alpha^j_{h,2}] + [I^j_t \boldsymbol{\beta}^j_{h,1} + (1 - I^j_t)\boldsymbol{\beta}^j_{h,2}]'\mathbf{X}_t + \epsilon^j_{t+h} \quad \epsilon^j_{t+h}|\mathcal{I}_t \sim N(0, I^j_t h^j_{t+h,1} + (1 - I^j_t)h^j_{t+h,2}),$$

where $I^j_t = 1$ if $S^j_t = 1$ and 0 otherwise. From an economic viewpoint, the assumption of two-state Markov switching (MS) dynamics implies that in each country, financial markets may switch between two alternative predictive environments. 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 (IP) may impact our forecasts of bond returns only when the bond market is in a bull state with high returns caused by declining interest rates as a result of 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. 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. We entertain both the case of $h^j_{t+h,1} = h^j_{t+h,2}$ – 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 – and the heteroskedastic case of $h^j_{t+h,1} \neq h^j_{t+h,2}$. We name the last case MSH to indicate that the Markov switching dynamics implies heteroskedasticity.[7]

3.4. *Threshold and Smooth Transition Regime Switching Models*

Although heavily employed 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

[6] It may be of interest to extend our results when more than two regimes are allowed, given recent evidence that three or more states would be required to fit and predict the dynamics of stock and bond returns; see Guidolin and Timmermann (2005) for U.K. evidence, and Guidolin and Timmermann (2006) for U.S. results. Section 6.4 discusses the possible costs of imposing $k = 2$.

[7] We impose two additional restrictions. First, we estimate the properties of the Markov state separately for stock and bond markets in each country (hence the notation S^j_t). As argued in Guidolin and Timmermann (2005, 2006) 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^j_t.

to consist of a Markov chain – with a number of difficulties of interpretation of the resulting state process. Given their popularity in applied econometrics, we therefore expand the family 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 on whether the transition variable is above or below the threshold:

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

i.e. each of the two regimes applies in dependence on whether $g(\mathbf{X}_t)$ exceeds or not a threshold c_j (to be estimated), where $g : \mathcal{R}^m \to \mathcal{R}$ is a function that converts the current values of the predictors in $\mathbf{X}_t$ into a value to be compared with the threshold c_j. 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 have increased by an amount exceeding some (endogenously determined) threshold c_j; otherwise high IP growth rates forecast positive future bond returns.

In addition to TAR models we also consider smooth transition regression models. Whilst the TAR model imparts an abrupt non-linear behavior depending on whether the threshold variable(s) 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 transition variable and the transition value. The general STR model is given by:

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

where $0 \leq F(\mathbf{e}'_i\mathbf{X}_t) \leq 1$ is the transition function and the i-th variable in $\mathbf{X}_t$ (selected by the product $\mathbf{e}'_i\mathbf{X}_t$) acts as the transition variable. 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 than 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 time 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^{bond}_{t+h} will be captured by a weighted combination of elements in $\boldsymbol{\beta}^{bond}_{h,1}$ and $\boldsymbol{\beta}^{bond}_{h,2}$.

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

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

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

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

and (8) reduces to the TAR model. As $\rho_j \to 0$, (7)-(8) becomes linear because switching is impossible.

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

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

where the parameters in (9) change symmetrically about c_j with $\mathbf{e}_i'\mathbf{X}_t$. If $\rho_j \to \infty$ or $\rho_j \to 0$ the ESTR model becomes linear, while non-linearities require intermediate values for ρ_j. This model implies that the dynamics obtained for values of the transition variable close to c_j differ from those obtained for values that largely differ from c_j.

A peculiar issue in estimating smooth transition models concerns the smoothing parameter, ρ_j, the estimation of which may be problematic. In the LSTR model, a large ρ_j results in a steep slope of the transition function at c_j, thus a large number of observations in the neighborhood of c_j are required to estimate ρ_j accurately. Additionally, as a result convergence of ρ_j may be slow, with relatively large changes in ρ_j having only a minor effect upon the shape of the transition function. A solution to this problem, suggested by Teräsvirta and Anderson (1992) is to scale the smoothing parameter, ρ_j, 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:

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

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. 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, using the STR)

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

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. 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 minimizes the sum of squared residuals, for instance

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

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: 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 predictors. 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 variable:

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

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_j. (10) becomes comparable to Markov switching heteroskedastic models in (4) because the second moment contributes to the definition of the regime, along with the conditional mean.[8]

3.5. *Other, Standard Benchmarks*

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 the existence of a constant factor of change in log-prices, i.e., $r^j_{t+h} = \ln P^j_{t+h} - \ln P^j_{t+h-1} = \alpha^j + \epsilon^j_{t+h}$ which implies

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

[8] 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.

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 atypical for $h > 1$. To increase the set of useful benchmarks, (11) and (12) are also estimated incorporating simple (Gaussian) GARCH(1,1)-in mean effects:

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

where $\epsilon^j_t|\mathcal{I}_t \sim N(0, h^j_t)$.

4. Evaluation 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 their appearance in a predictive regression), indirectly (through the definition of regime shifts, in non-linear models), or through a combination of the two – forecasting performance, 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 our goals.

Define the time t forecast error from model μ, at horizon h, and for asset j (i.e., 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 – linear and non-linear – defined in Section 4. For each combination defined by country, market, model, and horizon, we proceed to compute six difference measures of prediction accuracy ("performance"):

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

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

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

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

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

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

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

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

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:

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

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 values:

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

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 often argued in empirical finance, for many trading strategies it is more important that a forecast function may deliver predictions with a correct sign than predictions which are quantitatively very accurate (i.e., it 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 with an incorrect sign indication).

A simple ranking of forecasting models based on any of these six measures will not be exhaustive: the fact that model $\mathcal{M}_1$ proves more accurate than model $\mathcal{M}_2$ does not imply that the null hypothesis that the difference between $\mathcal{M}_1$ and $\mathcal{M}_2$ is zero may be rejected in statistical terms. We therefore employ four different methodologies to test whether any differences may be supported in statistical terms. The first of these procedures has been introduced by Mincer and Zarnowitz (1969) and takes the form of a simple regression:

$$r_{t+h}^j = \varphi_{h,0}^j + \varphi_{h,1}^j\hat{r}_{t,t+h}^{j,\mu} + \xi_{t,t+h}^{j,\mu}, \tag{20}$$

where $\xi_{t,t+h}^{j,\mu}$ is a martingale difference sequence with constant variance σ_ξ^2. A "good" (sometimes said to be unbiased) forecast model implies that $\varphi_{h,0}^j = 0$ and $\varphi_{h,1}^j = 1$ so that

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

(this means that forecast errors are martingale difference sequences, i.e. they have no structure); sometimes, it is also expected that the regression R^2 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 $\varphi_{h,0}^{j} = 0$ and $\varphi_{h,1}^{j} = 1$; (iii) the p-value from an F-test of the composite hypothesis that *simultaneously* $\varphi_{h,0}^{j} = 0$ and $\varphi_{h,1}^{j} = 1$.

Mincer and Zarnowitz's (1969) test heavily relies on parametric assumptions concerning $\xi_{t,t+h}^{j,\mu}$ and has only a weak connection to the practical uses of forecasts of stock and bond returns in financial markets. In particular, as discussed earlier, it happens that market traders may use forecasts not really to place bets based on the level 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 $\hat{P}_h^{j,\mu}$, an estimate of the probability that r_{t+h}^{j} and its forecast $\hat{r}_{t,t+h}^{j,\mu}$ have the same sign "conditional" on independence of r_{t+h}^{j} from its forecast:

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

where

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

The PT statistics is then computed as

$$PT_h^{j,\mu} \equiv \frac{SR_h^{j,\mu} - \hat{P}_h^{j,\mu}}{\sqrt{\widehat{Var}\left(SR_h^{j,\mu}\right) - \widehat{Var}\left(\hat{P}_h^{j,\mu}\right)}} \overset{a}{\sim} N(0,1), \tag{21}$$

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

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

Notice that a necessary condition for the PT test to be implementable is that not all the observations for r_{t+h}^{j} and its forecasts $\hat{r}_{t,t+h}^{j,\mu}$ 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 $\mathcal{M}_1$ and $\mathcal{M}_2$ 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:

$$diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2} \equiv L\left(e_{t,t+h}^{j,\mathcal{M}_1}\right) - L\left(e_{t,t+h}^{j,\mathcal{M}_2}\right). \tag{22}$$

The DM statistics is defined as

$$DM_{j,h}^{\mathcal{M}_1,\mathcal{M}_2} \equiv \frac{\frac{1}{T-h}\sum_{t=1}^{T} diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}}{\widehat{\sigma}\left(diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right)} \tag{23}$$

As in Guidolin and Timmermann (2008) to compute an estimate of the standard error of the loss differential by using the standard Newey-West estimator

$$\widehat{\sigma}\left(diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right)=\sqrt{\sum_{i=-h}^{h}\widehat{Cov}(diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2},diff_{t+i,j,h}^{\mathcal{M}_1,\mathcal{M}_2})}.$$

Note that the square of the estimate can be negative. When this rare event arises, as Diebold and Mariano (1995) suggest, we treat $\widehat{\sigma}\left(diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right)$ to be zero and automatically reject the null hypothesis. Diebold and Mariano (1995) also show that the DM statistics has an asymptotically normal distribution: $DM_{j,h}^{\mathcal{M}_1,\mathcal{M}_2}\overset{a}{\sim}N(0,1)$. Using the asymptotic normal distribution, the following one-side hypothesis test can be implemented:

$$H_o:\quad E\left[diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right]\leq 0 \Longleftrightarrow \text{model } \mathcal{M}_1 \text{ outperforms model } \mathcal{M}_2.$$

Of course, the same test procedure may be used to test the null that $E\left[diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right]\geq 0$, i.e., that model $\mathcal{M}_1$ under-performs model $\mathcal{M}_2$. In this paper we initially implement DM test assuming a square loss function, i.e.

$$diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}=\left(e_{t,t+h}^{j,\mathcal{M}_1}\right)^2-\left(e_{t,t+h}^{j,\mathcal{M}_2}\right)^2. \tag{24}$$

Van Dijk and Franses (2003) develop a weighted test of equal prediction accuracy by modifying Diebold and Mariano's (1995) test. The basic intuition of the van Dijk and Franses' (DF) test is that the loss function should assign more weight to extreme observations, therefore testing if a model is able to forecast outliers correctly. This seems a particularly compelling point when predicting financial returns, when large returns are particularly meaningful both for risk averse investors (who assign a higher marginal utility weight to losses than to gains) and for regulatory purposes (think of value-at-risk and capital requirement issues). By contrast, the standard DM test imposes equal weights on all observations. van Dijk and Franses introduce the following three types of weighting functions:

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

where $\phi(\cdot)$ is the probability density function of the forecast target variable, r_t^j, and $\Phi(\cdot)$ is the cumulative distribution function of the forecast target variable. Note that in general the weight can be any function of the history of the target and predictor variables. The first weighting function extensively penalizes forecast errors when observations take extreme values in both tails of the distribution; the second (third) weighting functions focusses instead on the left (right) tail of the distribution.[9] In practise, the probability density function in the first weight is computed by applying a kernel smoothing method based on the normal kernel function while the empirical cumulative distribution function is used for the other weights. DF suggest employing a standard Nadaraya-Watson kernel estimator to compute the $\phi(\cdot)$. As in van Dijk and Franses (2003), we employ all observations of the target variable in the whole sample period (1979:02-2007:01) to estimate $\phi(\cdot)$ and $\Phi(\cdot)$. Once a selection of a weighting function W_{it} is made, the DF statistics (sometimes also referred to

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

as a modified, weighted-DM statistic, W-DM), is given by a simple weighted average loss differential of two competing models, $\mathcal{M}_1$ and $\mathcal{M}_2$, divided by its standard deviation,

$$DF_{j,h}^{\mathcal{M}_1,\mathcal{M}_2} \equiv \frac{\frac{1}{145-h}\sum_{t=1995:01}^{2007:01-h} W_t \times diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}}{\widehat{\sigma}\left(W_t \times diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}2}\right)}. \tag{25}$$

In our paper, the DF statistics is computed with a square loss function and the three different weighting functions, the same suggested by DF in their original work. Similarly to the DM statistics, the DF statistics has an asymptotic standard normal distribution under the usual assumption of forecasting errors. In particular, the following one-side tests are performed:

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

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

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 $e_{t,t+h}^{j,\mathcal{M}_1}$ and $e_{t,t+h}^{j,\mathcal{M}_2}$ are usually generated from parametric models that have to be recursively estimated over time, i.e. $e_{t,t+h}^{j,\mathcal{M}_1}$ and $e_{t,t+h}^{j,\mathcal{M}_2}$ have to be themselves estimated using $\hat{e}_{t,t+h}^{j,\mathcal{M}_1}$ and $\hat{e}_{t,t+h}^{j,\mathcal{M}_2}$. This means that $\widehat{diff}_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2} = \left(\hat{e}_{t,t+h}^{j,\mathcal{M}_1}\right)^2 - \left(\hat{e}_{t,t+h}^{j,\mathcal{M}_2}\right)^2$ will be probably polluted by errors caused by estimation uncertainty concerning the parameters of the underlying models.[10] From a methodological point of view, GW shift the focus from the 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

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

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

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

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

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

[10] 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. Another advantage of GW tests is that they may not suffer from biases when competing models are nested: Corradi and Swanson (2007) and Golinelli and Parigi (2008) have recently argued in this sense.

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

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

functions $\mathbf{g}_t$, the null of equal conditional predictive ability (CPA) for a pair of models $\mathcal{M}_1, \mathcal{M}_2$ can be tested using the statistic

$$GW_{\mathbf{g}}^{\mathcal{M}_1,\mathcal{M}_2}(j,h) \equiv (T-h)\left[\frac{1}{T-h}\sum_{t=1}^{T}\mathbf{Z}_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h)\right]'\left[\hat{\mathbf{\Omega}}(Z_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h))\right]^{-1}\left[\frac{1}{T-h}\sum_{t=1}^{T}\mathbf{Z}_t^{\mathcal{M}_1,\mathcal{M}_2}(j,h)\right] \quad (26)$$

where

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

Under regularity conditions, $GW_{\mathbf{g}}^{(m,n)}(j,h) \overset{a}{\sim} \chi^2_{(q)}$. The power properties of the tests obviously depend on the choice of test functions in $\mathbf{g}_t$, although it is also clear that rejections of H_o' with respect to some set of functions $\mathbf{g}_t$ may give indications as to ways in which the forecasting performance could be improved. As in Giacomini and White (2006), we set $\mathbf{g}_t \equiv [1 \ \Delta diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}]'$ $(q=2)$.[13]

5. **Empirical Results**

Presenting results for such an extensive experiment such as ours faces one challenge: with 20 alternative econometric frameworks to be compared, 7 countries yielding two series of stock and bond return data, and five alternative performance measures, it is impossible to provide a detailed account for all the results. In fact, when one considers that in this paper we have computed forecasts for three alternative horizons – $h = 1$, 3, and 12 months – a simple calculation reveals that we have obtained a minimum of 5,040 values for predictive accuracy measures of different types. Even when it comes to comparing – for each given country and market, and after selecting a forecast horizon – the relative forecasting performance by testing for equal predictive accuracy, it easy to determine that with 20 models, tests can be performed for as many as 190 pairs of models. This means that in total as many as 7,980 comparisons have been performed. Therefore in this Section we proceed by successive refinements. In Section 5.1 we briefly describe our recursive forecasting experiment. In Section 5.2 we summarize the main results by focussing our attention only on the "winners", i.e. – per each country and asset-type – the three models that produced the best forecasts. In Section 5.3 we comment results country by country and make our best effort to flesh out the key empirical results delivered by our analysis. In Section 5.4 we formally test for superior predictive accuracy by systematically testing the null of equal accuracy for all possible pairs of models. In Section 5.5 we investigate whether predictive performance as well as rankings across models vary over time. Guidolin et al. (2008) report additional results, comments, and full tabulation of all our empirical findings. We direct the interested Reader to that paper for further details and insights.

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

We consider a pseudo out-of-sample experiment. We recursively estimate 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.

[13] We also compute CPA tests when $\mathbf{g}_t \equiv [1 \ \Delta dif f_t^{(m,n,h)} \ \Delta dif f_{t-1}^{(m,n,h)} \ e_t^{(m,h)} \ e_{t-1}^{(m,h)} \ e_t^{(n,h)} \ e_{t-1}^{(n,h)}]'$, 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.

up to the last possible available sample, 1979:02-2007:01. An initial sample of approximately 16 years of monthly observations guarantees the availability of a sufficient number of observations even in the presence of a large number of parameters to be estimated (up to 24 in the case of the MSH model). At each date we produce asset return forecasts for two alternative horizons, $h = 1$ and 12 months. For instance, at the end of 1995:01 we compute forecasts for stock and bond returns for 1995:02, 1995:04, and 1996:01. This implies that for each combination of model, horizon, country, and asset-type one will produce $145 - h$ forecasts to be recorded and used for evaluation purposes (i.e., 144 for 1-month and 133 for 12-month horizon forecasts).

5.2. *An Overview of Forecasting Performance*

Table 2 synthetically presents the bulk of our results: for each country and each of the six performance measures described in Section 4, we report the three best performing models found in our (pseudo) out-of-sample forecasting exercise. The first panel of Table 2 (especially when compared to the remaining panels) shows one 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 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 (2003, 2005, for the U.K.). The excellent RMSFE performance derives from the fact that Markov switching (MS) models produce a 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 fact, especially at 12-month forecast horizons, other non-linear prediction frameworks (such as ESTAR) and ARCH-in mean models 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. We also notice that, at least at the 1-month horizon and for U.S. equities, also the Gaussian threshold GARCH(1,1)-in mean model yields appreciable accuracy, although in most metrics it comes in third after the Markov switching models; in the case of U.K. equities, a similar role seems to be played by the Logistic STAR model in which the transition variable is the short term interest rate.

Panel A of Table 2 shows that the evidence is slightly more mixed when it comes to forecasting bond returns in the U.S. and the U.K. 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 performance measure) also TAR and STAR models offer a good predictive performance, along with the simpler benchmarks. In particular, this seems to be the case when the performance is measured in terms of MPFE. However, MS and MSH models remain important outperformers at predicting bond returns, when one looks at the Success Ratio, which in principle it may be the most relevant criterion for a trader.

All in all, panel A of Table 2 shows that non-linear models may not be easy to dismiss in terms of out-of-sample performance for the Anglo-Saxon markets. For instance, out of a total of 144 "cells" in panel A of Table 2 (which means that we would be putting on equal footing U.S. and U.K., 1- and 12-month horizons, stocks and bonds, and the fact that a model may have been ranked first, second, or third), we notice that Markov switching models appear 76 times, i.e. in 53 percent of the cells (but notice that MS and

MSH may at most take up 96 cells, which implies that the 76 appearances actually represent a 79 percent of the possible total); additionally, TAR and STAR models appear in 23 cells, for a combined 69 percent of the total. Only in 19 cases (i.e., in 13 percent of the possible occurrences), one of the simple benchmarks ranks among the three best models; among the benchmarks, the random walk with drift – which implies the absence of any predictability for stock and bond returns – seems to be prominent, appearing 11 times. This is partially consistent with the well-known result in the empirical finance literature that in many occasions asset returns would be unpredictable.[14] Remarkably, in only three cases a simple linear regression provides accurate forecasts according one of the six metrics we have proposed. Finally, the difference between 144 and the 119 spots taken up by Markov switching, threshold, and simple benchmark models is represented by cases in which combinations between simple random walk, AR(1), linear predictive regression and ARCH-in mean models delivers "top three" performances. This seems to happen particularly frequently for U.K. stock returns.

Looking at panels B and C of Table 2 allows us to contrast the top performance of Markov switching models in predicting U.S. and U.K. returns to the results obtained for the remaining G7 countries. In the case of Japanese stock returns (panel B), the performance of the LSTAR model when the transition variable is the short-term T-bill rate change is generally very strong. In the Japanese case, MS and MSH remain accurate models, but only in a few metrics (such as 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 RMSFE metric and, for similar reasons, also in the MAFE metric. In quantitative terms, these points are made clear by the fact that in 27 cells out of 72, threshold models turn up among the best-three performers across criteria and markets, followed by 16 occurrences each for both the simple benchmarks and for random walk and linear prediction models that also feature ARCH-in mean effects. The latter are particularly good when forecasting bond returns. MS and MSH appear only in 8 cases. A naive, linear predictive regression model produces accurate performances only for Japanese stock returns and mostly for 12-month horizons.

Results for German stock returns are very hard to summarize in a useful way: with six criteria and three podium spots available (for a total of 18 winning models that can be reported), at least a dozen models show some "top" level performance. However some weak indications may 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 different types) are excellent at 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 and linear predictive regressions, although in many cases the presence of a GARCH-in mean effects improves performance; in the case of Germany, a simple homoskedastic AR(1) offers good performance. Non-linear models (especially TAR and STAR) are only useful to minimize MPFE and 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. Quantitatively, in more than half of the cells (37) available to pick up top-three performance, we find some type of threshold model for the conditional mean; however, while for German

[14] However, we need to stress that 11 occurrences represent only less than 8% of the total. Let us add that the random walk model fails to be included in the set of models useful for forecasting applications in the U.S. and the U.K. in another sense: in only 2 occasions, random walk models with ARCH-in mean effects enter the best-three rankings presented in Table 2.

stocks this tends to occur mostly under a RMSFE criterion and for longer horizons, for German bond returns the patterns are less clear. Also in this case, simple benchmarks would be of limited use, taking up only 14 (19 percent) of the cells, with naive linear homoskedastic predictive regressions appearing only 5 times and generally in third position.

Panel C of Table 2 strengthens our impression that the forecasting performance depends on the country and the asset market under investigation and that the finding that MS models offer a top performance in the case of the U.S. and the U.K. is an interesting result that cannot be generalized. The panel that refers to France, Canada, and Italy reveals that in these cases the need of non-linear frameworks in forecasting applications is weak. In the case of French bond returns, there is weak evidence of non-linear behavior; simple benchmarks (with at 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. In fact, out of 36 cells signalling top performance, 16 go to simple benchmarks, while in 9 additional cases, augmenting the random walk and simple linear prediction models with ARCH-in mean effects, gives accurate predictions. The evidence for French stock returns is mixed, although it is remarkable that in 11 cases we find evidence of accurate forecasting performance from linear predictive models augmented by ARCH-in mean effects.

Also for Canadian asset returns, simple benchmarks 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, non-linear models are definitely needed at all horizons to minimize the MPFE. In fact, out of 72 cells to be used to indicate top performances, 30 go to threshold-type models, with a slight prominence of logistic STAR models. This number is followed by the 21 cells that get assigned to the random walk and the AR(1) benchmarks, while in 14 other circumstances the random walk and the linear predictive regression seem to benefit from the use of ARCH-in mean terms. In particular, for Canadian bond returns, benchmarks or ARCH-in models perform best over short horizon, but LSTAR models are best over long forecast horizons. In the Canadian case, MS and MSH models hardly appear among the best performing.

Not surprisingly, results for Italy are almost opposite of U.S. results, in the sense that the need for non-linear modeling largely disappears: even pulling together smooth – of all types, logistic, exponential, etc. – and simple threshold models together with MS and MSH models, we have that in only 21 cells (29 percent of the total) the non-linear frameworks exhibit top performances. On the opposite, the simple benchmarks rank very high, accounting for 19 of the top performances, while ARCH-in mean-augmented random walk models enter the three-best performing models in another 21 cases. However, this does not mean that adopting naive linear predictive homoskedastic regressions may be a useful forecasting strategy, as this model provides good performance only in three cases, similar to what happens for Canada (only one case) and France (3 cases).

5.3. *Country and Asset Specific Results*

Table 3 gives detailed results on predictive performance for each country and for stock and bond returns, separately in different panels of the table. In the following we preferentially report comments related to RMSFE, the Pesaran-Timmermann's, and Mincer-Zarnowitz's tests for the case of $h = 1$; we discuss other performance criteria and $h = 12$ results only when findings are different and/or interesting enough. To save space, we only report comments concerning patterns common across countries and markets, with the understanding that with 20 forecasting models, 7 countries, two asset markets, and using six criteria supplemented by 3-4 approaches to test for differential predictive accuracy, the mass of available results is huge. First, while for U.S. and U.K. stock returns the differential RMSFE performance of the best models (MS and MSH) compared to the followers is large (e.g., 3.6-3.7% at $h = 1$ under Markov switching vs. 4.1% and higher for other models), for the other five countries as well as for U.S. and U.K. bond returns the differences are small (e.g., the three best models to forecast Japanese returns give performances between 5.0 and 5.1 percent, while the worst model yields a 5.3 percent). Importantly, for U.S. and U.K. stock returns, these major differences are unaffected by considering $h = 12$. Second, if one wants to decompose the RMSFE ranking in terms of bias vs. variance contribution, Table 3 reveals that the most important factor underlying top RMSFE performance is variance and not bias. This implies that in many occasions, the best RMSFE models are not those with the smallest bias (in absolute value), while on the contrary the association between top RMSFE performances and forecast error variance minimization is stronger. For instance, in the case of U.K. stock returns, we see that the for $h = 1$ the three models minimizing bias do not coincide with the three models that minimize RMSFE; however, the three models minimizing variance coincide with the three top models (MS, MSH, and LSTAR when the threshold variable is the lagged changed in T-bill yields).[15] Correspondingly, the differences between minimum forecast error variances (usually associated with MS modes) and the remaining models is very large for U.S. and U.K. stock (and to a lesser extent, bond) returns. Third, there appears to be a difference between results for U.S. and U.K. stock returns and other countries and markets in one additional dimension: while for Anglo-Saxon stock returns, RMSFE and MPFE results are similar, in the sense that the models that produce low RMSFEs are in generally also the ones that minimize the (absolute value of the) MPFE, this alignment does not occur in most other cases. For instance, already for U.S. bond returns and at $h = 1$, it is ARCH-in mean and threshold models that minimize the MPFE (to a stunningly low -0.021% per month in the case of a TAR in which the threshold variable is the predicted bond return). Another case in which the differences in the RMSFE- and MPFE-metrics are substantial is for Italian stock returns: while ESTAR and LSTAR models deliver the lowest MPFEs (in the range 0.49-0.74 percent per month), the best RMSFE models are the random walk (with and without ARCH-in mean effects) and a AR(1) GARCH(1,1)-in mean. Of course, market operators interested in using models that produce prediction errors that tend to remain in some way "proportional" to values to be predicted and such that negative and positive errors tend to compensate (when scaled by the values they aim at predicting), may be selecting models on the basis of their MPFE and not of their RMSFE. Fourth, notice that (especially for $h = 1$) for U.S., U.K., Japanese, Italian stock and bond returns as well as for German and French bond returns the rankings of models provided by MAFE and RMSFE tend to largely coincide. In these cases, squaring or taking the module of forecast errors does not seem to be of large importance for whether non-linear or linear models provide the best prediction performances.

As explained in Section 3, in Table 3 we also proceed to compute the Success Ratio (SR) and to test whether the ratio is significantly different from what one would obtain under the null that actual returns and predictions are independent of each other. Results are qualitatively homogeneous with those we have reported for the RMSFE, in the sense that non-linear models (particularly, MS models) are called for in the case of U.S. and U.K. financial markets (especially by stocks), while for most other countries there is no clear

[15] Of course, this is a just an average pattern, in the sense that cases can be found in which the association of good RMSFE performance with both bias and variance is weak (i.e., it is a combination of the two that minimizes RMSFE). For instance, to some degree this happens for Italian bond returns.

discernible pattern.[16] For U.K. and U.S. markets, the values of SR achieved by MS models are impressive, as high as 75-80%; what is even more striking is that such values are often also reached for $h = 12$, when the prediction problem is clearly harder. For the remaining countries the best SRs are typically between 60 and 70 percent, which confirms the existence of a higher degree of predictability – but only as captured by relatively sophisticated non-linear frameworks – in the Anglo-Saxon markets. Table 3 also reports Pesaran-Timmermann market timing tests; boldfaced values of the statistic indicate statistical significance with p-values of 5% or lower. Notice that – because when all the observations on asset returns and the corresponding forecasts have the same sign, the PT statistics is not defined – for a few of the models and horizons the PT test could not be implemented. The qualitative indications are once more consistent with the results obtained for the RMSFE. For the U.S. and the U.K. markets we have indications that independently of the horizon, MS models give statistically significant and exploitable sign indications. Occasionally a few of the non-MS models (especially the simple benchmark) display negative information contents for market timing, i.e., the associated PT statistic is negative and statistically significant. For Japanese returns, the indications are weak at short horizons, but some market timing potential (especially for stock returns) emerges for a number of non-linear models at $h = 12$ months, including MS frameworks. Market timing performance is weaker for the remaining countries: for instance, in the case of French and Italian bond returns, none of the SRs generates a statistically significant PT; the evidence is also thin in the case of Italian stock and Canadian bond returns. Cases can be found in which most of the favorable market timing evidence actually points in the direction of either simple benchmark models or ARCH-in mean frameworks (e.g., for French stock returns).

Finally, Table 3 presents four different outputs from Mincer-Zarnowitz (MZ) regressions: the regression R^2, the p-values from standard t-tests of the separate null hypothesis that $\varphi_{h,0} = 0$ and $\varphi_{h,1} = 1$, and the p-value from an F-test of the composite hypothesis that simultaneously $\varphi_{h,0} = 0$ and $\varphi_{h,1} = 1$. Once more, U.S. and U.K. results are structurally different from results obtained from the rest of the countries. In the Anglo-Saxon markets, MS models yield interesting double-digit MZ R^2, from 14% in the U.S. bond market up to 47% (at $h = 12$) for U.K. bond returns. Importantly, there is a substantial difference between MS models and the remaining bunch of linear and non-linear models that can hardly generate MZ R^2s close to 10%. For the remaining 10 pairs of countries and asset markets, we systematically find that even the highest R^2s never reach 10%, although in some cases among the highest R^2s we find non-linear models (especially at $h = 12$). In this perspective, we can say that our forecasting efforts are partially successful only in the Anglo-Saxon markets, and much less useful for the remaining G7, as even the best prediction models fail to explain even one-tenth of the variance of asset returns. The evidence from statistical tests concerning the MZ coefficients $\varphi_{h,0} = 0$ and $\varphi_{h,1} = 1$ shows that it is comparatively easier to fail to reject unbiasedness at a 12-month than at a 1-month horizon, that biases in forecasts tend to be stronger for bonds than for stocks, and that in many cases all models produce biased forecasts (this is the case of U.K. bond returns at all horizons, and largely for French bond returns).[17] Although MS models generate unbiased forecasts of U.S. returns, it is interesting to notice that this is not really the case for U.K. returns (in particular at $h = 12$). In the Japanese case, we notice that it is relatively easy to fail to reject the hypothesis that $\varphi_{h,0} = 0$ while $\varphi_{h,1}$ systematically fails

[16] However, for French bond, and Canadian, and Italian markets there is evidence that the highest SRs are returned by simple benchmarks, such as the random walk (with and without ARCH-in mean effects) and a simple AR(1).

[17] On the contrary, most models produce unbiased forecasts in the MZ sense in the case of German and French stock returns. This is interesting also because for these two markets the MZ R^2 are at most 3-4%.

to be 1; the joint hypothesis of $\varphi_{h,0} = 0$ and $\varphi_{h,1} = 1$ tends in fact to be not rejected for simple benchmark models, showing that while non-linear frameworks produce accurate forecasts, they also contain systematic biases, illustrated by the fact that realized values fail to move one-to-one with predicted values (this is the implication of $\varphi_{h,1} \neq 1$).

5.4. *Testing for Differential Predictive Accuracy*

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. The many panels of Table 4 are organized in the following way: *above* the main diagonal, in each cell we report DM p-values for the null hypothesis of identical predictive accuracy for the models that "intersect" in correspondence to the cell; *below* the main diagonal, in each cell we show the GW p-value for the null hypothesis that $E_{t-1}\left[diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2}\right] = 0$, i.e., that the instruments in the information set contain no information to predict loss functions differentials. For instance, in panel A (United States, $h = 1$), the 0.368 in the cell at the intersection between the homoskedastic linear predictive and the random walk models, indicates that the null of no difference in prediction accuracy between the two models cannot be rejected at standard significance levels of 5% or lower, i.e., the forecasting performance of the two models is not significantly different. As another example, the 0.017 at the intersection between "MS two-state heteroskedastic" and the AR(1) with GARCH(1,1)-in mean effects in the last row of panel B (U.S., $h = 1$), shows that the null of no predictive power from the instruments to the difference in loss functions between the models may be rejected using tests of size between 1 and 5 percent, but not with tests with size of 1 percent and lower. Clearly, in the presence of 20 different models, there are 190 different intersections/pairs of models for which the DM and GW tests may be applied, yielding a wide range of results.[18] At least initially, we use the MSFE metric as a way to capture the notion of "accuracy" in forecasting, as in the bulk of the literature, i.e., we set $diff_{t,j,h}^{\mathcal{M}_1,\mathcal{M}_2} = (e_{t,t+h}^{j,\mathcal{M}_1})^2 - (e_{t,t+h}^{j,\mathcal{M}_2})^2$; section 6.2 removes this assumption.

In Table 4 it is of some interest to go over the results on a country-by-country basis. For the U.S. and a short forecast horizon (panel A), both DM and GW reveal the existence of statistically significant evidence that the two MS models (in particular, the MS homoskedastic model in the case of GW) are significantly more accurate than all other models entertained in this paper. The only partial exception occurs with reference to the TAR model when the threshold variable is represented by the lagged, predicted stock returns themselves: according to DM, this model cannot be easily told apart from MS and MSH in statistical terms, since the p-values are between 0.05 and 0.10. Interestingly, neither DM nor GW can actually distinguish between the predictive performance of MS and MSH models, i.e., although point-wise, the RMSFE in Table 3 had revealed that fitting a regime-switching variance components does not help the accuracy of mean forecasts, these differences are hardly significant in statistical terms. Finally, it is hard or impossible under both DM and GW to distinguish between the performances of different benchmarks, as well as between alternative ARCH-in mean models. Panel B, for the U.S. case with $h = 12$, implies an interesting dichotomy between DM and GW test results: while DM keeps showing that MS and MSH are more accurate than all other

[18]Notice that for both DM and GW tests, the transitive property does not hold, i.e., the fact that the model $\mathcal{M}_1$ predicts significantly better than model $\mathcal{M}_2$ and that model $\mathcal{M}_2$ predicts significantly better than model $\mathcal{M}_3$, fails to imply that model $\mathcal{M}_1$ is statistically significantly more accurate than model $\mathcal{M}_3$. However, a careful scan of all the panels in Tables 4 and 5 reveals that no such embarrassing reversals have occured in our experiments.

models, GW stops giving any significant indications, as the p-values involving MS and MSH now climb up to levels between 0.10 and 0.30. This means, that once the persistence in MSFE differences is taken into account through the GMM-style testing approach of GW, all evidence of superiority in favor of Markov switching models considerably weakens. Strikingly, results for U.K. stock returns are qualitatively very similar to those obtained for the U.S.: there is substantial evidence favoring the predictive accuracy of MS and MSH; however, the other non-linear framework that now partially resists to their supremacy is a Logistic STAR framework in which lagged T-bill yields drive the (smooth) threshold switching. Importantly, in panels A-D we notice that at least one non-linear models can always be found that – both under the DM and the GW metrics – produces significantly more accurate forecasts than a naive random walk, with or without ARCH-in mean effects.

Contrary to the remarks expressed with reference to Table 3, the Japanese stock returns results in panels E and F and for Canada in panel I mark a substantial discontinuity vs. panels A-D: at $h = 1$, there is very little or no evidence that any of our models significantly outperforms the remaining models; this means that although in Table 3 we had some evidence that non-linear forecasting could be useful for the Japanese equity market, none of these evidence is sufficiently strong to withstand formal statistical testing. In panel F, for $h = 12$, we have another interesting dichotomy between DM and GW: while the latter still reveals weak signals, in a DM metric we find that the Logistic STAR (T-bill) model outperforms roughly half of the remaining models (but not the other non-linear frameworks). The results obtained for German and stock returns are qualitatively similar to those commented for Japan and Canada, with the only difference that the non-linear model that now gives indications of some superior predictive accuracy at $h = 12$ is the ESTAR model, once more with lags short-term rates as the variable governing smooth transitions.[19] French stock returns appear to have once more a similar characterization, although the roles of $h = 1$ and $h = 12$ are not flipped, i.e., there is some evidence of superior predictive accuracy in favor ESTAR and LSTAR models (with lagged T-bill yields driving transitions), but only for short-term forecasts. However, also in this case DM and GW tests cannot tell different non-linear models apart from each other. Finally, Italian stock returns not only contain at best weak evidence of predictability, but it is also the case that the models are hardly distinguishable in the sense that DM and GW do not allow to single out models that significant outperform any of the competitors.

Table 5 performs the same tests of Table 4, but focusses instead on predicting bond returns. To save space, in this case we only report results for the case $h = 1$ and use comments to signal cases in which (unreported) results are any different.[20] Panels A-C (for the U.S., and the U.K., respectively) trigger comments which are similar to those for panels A-D of Table 4: both DM and GW show that MS and MSH models are significantly more accurate in a MSFE metric than any of the other models considered, including ESTAR and LSTAR models. In fact, for U.S. and U.K. bond returns, results are even stronger than in the case of equity returns, as the p-values reported tend to be smaller (generally between 0.00 and 0.01), and in at least one case (when the DM test is used on U.S. results) it reveals that a MSH model is significantly more accurate than a MS model.[21] At intermediate forecast horizons of 12-months, while any evidence of superior predictive

[19] Panel G of Table 4 focuses on the $h = 1$ case only, as planned. Detailed results for $h = 12$ are available upon request from the authors. A similar comment applies to panel I, concerning Canda.

[20] The only exception is for the U.S., where also the results for $h = 12$ are reported in panel B.

[21] In the U.S. case (panel A) there is also some evidence favorable to the LSTAR model (with switching governed by lagged predicted bond returns) when DM tests are applied, and to the TAR (with threshold variable given by lagged stock returns) model when GW tests are applied.

accuracy disappears in the case of the U.S. bond market, the U.K. DM results show that ESTAR models in which transitions depends on lagged short-term rates may be superior to a number of other models (including predictive regressions with and without ARCH-in mean effects), but not MS and MSH. Results for Japanese, French, and Italian bond returns are also similar: there is not sufficient evidence in favor of any of the models entertained, in the sense that panels D, F, and H reveal that rarely the pair-wise comparisons generate any statistical significant results.[22] On the contrary, for German and Canadian bond returns, the data contain sufficient information to discriminate among alternative models and in favor of threshold-type frameworks. For both countries, DM tests imply that a LSTAR model in which a predicted GARCH(1,1) variance serves as the threshold variable is significantly more accurate than most other models, including other, different non-linear frameworks. In the case of German bonds, the same results also obtains using GW. Additionally, something similar occurs for the LSTAR model in which switches are driven by lagged forecasts of bond returns themselves (but this model is anyway inferior to an LSTAR in which a GARCH(1,1) variance controls the switches).[23]

Table 6 reports results from DF tests when the weighting function is symmetric ($W_{1t} = 1-\phi(r_t^j)/\max\{\phi(r_t^j)\}$) and therefore gives additional weight to the ability of a model to correctly forecasts values in both tails. Once more, we save space by reporting results for $h = 1$ only (but we report selected comments concerning the $h = 12$ case).[24] Therefore we can now afford to use one table panel per country, reporting results for stock returns above the main diagonal and results for bond returns below the main diagonal. Panels A-C for the U.S. and the U.K. simply confirm earlier conclusions reached under standard, equally-weighted DM tests: MS and MSH significantly outperform all other models estimated in this paper, for both stock and bond returns. In the case of U.S. bond returns, there is statistically significant evidence favoring MSH over MS, which is not completely surprising because allowing variances to be a function of the regimes may help forecasting returns in the tails. Interestingly, at $h = 12$ and for U.S. stock returns, we also have some indication of the fact TAR and STAR models may be more accurate than ARCH-in mean models; at $h = 12$ for U.K. bond returns, DF tests yield that TAR and STAR models are often less accurate than simple benchmarks and ARCH-in mean models. Since these two results had not appeared in tables 4 and 5, we take this as an indication that TAR and STAR models at intermediate horizons not only fail to provide the lowest MSFE, but they also seem to systematically miss out on the prediction of stock and bond returns in the tails of their empirical distributions, which further accentuates the excellent performance of Markov switching models.

Panel D-H cover the remaining G7 countries. Similarly to Tables 4 and 5, the statistical evidence turns much weaker so that it becomes more problematic to try and argue that either non-linear or ARCH-in mean models are actually needed to produce superior (pseudo-) out of sample forecasts. In fact, for two countries, Canada and Italy, there is almost no useful information in our time series of return predictions to be able to tell the different models apart from each other.[25] For Japan, Germany, and France, the evidence is mixed

[22]This finding generally holds also at $h = 12$. The only exception is the fact that there is mild evidence of simple linear predictions outperforming other benchmarks and ARCH-in mean predictions in the case of Japanese bond returns, using DM tests.

[23]This evidence weakens when going from $h = 1$ to $h = 12$ in the German case. This does not occur for Canadian bond return forecasts, where there is still rather strong DM evidence of superior accuracy from a LSTAR-GARCH(1,1) model.

[24]Also in this case, we report complete results for U.S. forecasts.

[25]The only minor exception is that for Canada at $h = 12$ there is some evidence in favor of threshold models over simple benchmarks and ARCH-in mean frameworks for both stock and bond returns; LSTAR models are in particular evidence. Since this evidence is similar to what obtained in Tables 4 and 5 from standard DM tests, this indicates that LSTAR frameworks are

but generally similar (and weaker) than what we were able to report in Tables 4 and 5. For instance, while at $h = 1$ it is hard to establish any ranking using Japanese data, at $h = 12$ and for equity return prediction we obtain some evidence that LSTAR models with smooth transitions governed by past short-term rates may significantly outperform simple benchmarks as well as ARCH-in models; however, it remains problematic to obtain significant results within the non-linear class of models. In the case of Germany, at $h = 1$ there is evidence that a few threshold models may be significantly worse than simple benchmarks are predicting stock returns. Finally, in the French equity case, at $h = 1$ we obtain some evidence in favor of LSTAR models (again, in which lagged T-bills yields govern transitions); interestingly, this is consistent with the equally-weighted DM results in Table 4, while this is not the case for the performance of ESTAR models, implying that only LSTAR frameworks provide a robust performance at forecasting stock returns from the tails of their empirical distribution. All in all, we take the evidence in Table 6 as suggestive that our basic conclusions on the importance of modeling nonlinearities in financial forecasting applications are fairly robust to adapting the Diebold and Mariano's (1995) methodology to over-weight the prediction outcomes for returns in the tails, which may be of the utmost importance in financial decision-making. Section 6.3 to follow further investigates whether – for the purposes of the implementation of van Dijk and Franses' (2003) tests – considering the left vs. the right tails may make any additional differences.

5.5. *When Are Returns Predictable?*

So far, our provisional answer to the question "*where* are stock and bond returns predictable, in particular using non-linear models?" has singled out the U.S., the U.K., and – at least to some extent (mostly to predict stock returns) – Japan, Germany, and France as the countries in which non-linear frameworks seems to yield the best (pseudo-) out-of-sample results. In this section we ask instead *when* are stock and bond returns predictable, in particular using non-linear models. To this end, we break down our 23-year pseudo-out-of-sample periods in three sub-periods of identical length (48 months each in the case of $h = 1$ and 44 months each for $h = 12$) and examine results in Tables with structure affine to Table 3 to detect whether there any substantial differences in the sub-sample rankings across models. To make the tables readable, we report only a limited number of predictive accuracy measures and in the case of Mincer-Zarnowitz regressions, we limit ourselves to show the regression R^2 and the outcomes of a joint hypothesis test that $\varphi_{h,0} = 0$ and $\varphi_{h,1} = 1$. Again, for reasons of space we illustrate only results that concern the $h = 1$ case (which is likely to be most relevant for financial decision making) for U.S., U.K., Japan, and Germany, and comment on the remaining findings only when they are different from those obtained for $h = 1$.[26]

Panel A of Table 7 concerns results for the U.S. but we shall use it also to make a few general points concerning time-variation in relative forecasting performances. The basic result that non-linear models (MS and MSH) provide top-level forecasting performances holds across the three sub-samples; as it was true in Table 3, such accuracy mostly derives from the fact that Markov switching models minimize the variance

robust to overweighting returns in the tails of their empirical distributions.

[26] We also experiment with DM and GW tests over sub-periods, but the general finding seems to be that with a limited number of observations (e.g., 48 in each period for $h = 1$) it is impossible to reject the null of identical predictive accuracy of most possible model pairs. The only exception seem to be that for the U.S. and the U.K., even for many sub-samples there remains some evidence of significantly more accurate forecasting performance from Markov switching models, with p-values typically between 0.01 and 0.05. Detailed results are available upon request.

of forecast errors, and not really from their ability to minimize the absolute value of the prediction bias. Additionally, the "distance" between Markov switching and other models is rather large when predicting equity returns, and considerably more modest when it comes to bonds. However, there are also differences in forecasting performance across sub-periods that deserve some emphasis. For the U.S. equity market, RMSFEs are generally much smaller (roughly half) for the recent 2003-2007 sample than for the other two periods we have examined. In this sense, the predictability of stock returns seem to have enormously increased in recent times. This increase is entirely due to fact that the variance of forecast errors has substantially declined, to roughly one-fourth relative to 1995-1998, and to a stunning one-sixth vs. the 1999-2002 period. Interestingly, this is not the pattern displayed by the SR measure: in fact, the best achievable SRs are higher for the early 1995-1998 period (in excess of 80%) than for the later 2003-2007 period, although the SR touches bottom in the turbulent 1999-2002, with levels of 60% at best. On the opposite, the best achievable bond RMSFEs do not seem to have appreciably changed over time (if anything, they have moderately increased), although bond SRs patterns are similar to those commented for stocks. In fact, equity forecasts are so good in the recent 2003-2007 period, that their prediction error variance for stocks and bonds is approximately identical. In panel B, sub-sample recursive forecast results for the U.K. show similar patterns to panel A, although they tend to be weaker. However, also for the U.K., the good performance of non-linear models (among them, in particular MS and MSH) does not appear to be the product of any sub-period in particular.

Panels C-D show sub-sample results for Germany and Japan, to provide a sample what can be obtained outside the Anglo-Saxon markets. Germany and France display interesting structure that is worthwhile discussing. In the case of Germany, the non-negligible role for non-linear models we have found in Table 3, mostly derived from the post-1999 period, since over 1995-1998 it is either ARCH-in mean (for stock returns) or simpler benchmarks (bonds) that provide the highest accuracy. However, even after 1999 there is substantial evidence that for German asset returns, ARCH-in mean models are often useful. In terms of overall predictability, we observe the same U-shaped pattern – i.e., 1995-1998 and 2003-2007 imply stronger predictability – described in panels A and B; in fact, during the 1999-2002 sub-period RMSFEs and forecast error variances shoot up to double those computed for the 1995-1998 and 2003-2007 periods, while also the SRs decline from upwards of 70% to 50% for stocks and 65% for bonds. In the case of France, we observe a clear separation between the patterns of the first sub-sample – when STAR models prevail in forecasting stock returns and simple benchmarks are best for bonds – the second period – when for both stocks and bonds simple benchmarks perform best – and the third period, when most models perform similarly. In terms of SRs, predictability is maximum over the period 1995-1998 for both stocks and bonds. Finally, in the case of Japan, Canada and Italy, we fail to detect any special patterns: although the results in Table 3 are by construction the average of findings for each of the three sub-samples, it is difficult to isolate which particular periods may lead to the conclusions we have drawn and reported earlier. For instance, in the case of Japan (panel C) we have an overall, clear indication that the "amount" of predictability (especially for stock returns) is considerably lower in all sub-samples when compared to the Anglo-Saxon cases in panels A and B; for instance, even the best SRs are at least 10% lower than those found in panels A-B. In the first two sub-periods, there is evidence favorable to simple benchmarks, for both stock and bond return predictions. Interestingly, while in RMSFE terms the predictability of bond returns has improved over time, the best achievable SRs seem to decline over time.

All in all, although a few interesting patterns could be found, it does not seem that the role for non-linear models we have detected in Section 5.2 depends on any particular part of our sample or, better, it does depend on portions of our overall sample that are specific to each country under examination. However, at least for five out of seven of the countries examined, we have uncovered that the more turbulent 1999-2002 period implies a lower amount of predictability (both in terms of RMSFEs and of SRs) than the remaining two periods; in this sub-intervals, it tends to happen more frequently than not that the simpler benchmarks that minimize the need of estimation of parameters and that refrain from committing to specific forms of non-linearities may have been slightly more successful than more complicated and generously parameterized models.

6. **Additional Results**

In this Section, we summarize the results obtained from a few additional experiments and tests of superior predictive accuracy. Section 6.1 briefly considers whether our results are robust to expanding the set of models entertained in a few additional, yet natural directions. Section 6.2 performs DM tests when the loss function stops being symmetric and is replaced by a standard linex loss. Section 6.3 devotes some discussion to how results may be affected by taking into consideration that a number of model pairs are in fact nested. Finally, Section 6.4 briefly comments on the results obtained from asymmetric DF tests.

6.1. *More Prediction Models*

We experimented with a few additional models besides the 20 on which have extensively reported so far. In particular, we have used a small set of five additional models to check whether our results are robust to two choices made in Section 4. First, our earlier analysis has implemented AR(h) models that do not fit what a Reader may commonly interpret as an autoregressive time series model. In Section 4, we set the autoregressive benchmark to be $r^j_{t+h} = \alpha^j + \beta^j r^j_t + \epsilon^j_{t+h}$, which implies that for $h > 1$ forecasts are produced applying the direct method. We therefore proceed to also estimate classical autoregressive models,

$$r^j_{t+1} = \alpha^j + \beta^j r^j_t + \epsilon^j_{t+1}, \tag{27}$$

and compute h-month ahead forecasts indirectly, by simply iterating over the model in (27).[27] This traditional, indirect recursive way to produce forecasts is in fact also applied to the AR(1)-GARCH(1,1) in mean model (with Gaussian shocks), thus reinstating a complete symmetry between the indirect and recursive way in which we have treated predictions of standard deviations in $r^j_{t+h} = \alpha^j + \beta^j r^j_t + \gamma\hat{\sigma}^j_{t+h} + \epsilon^j_{t+h}$ and the forecasts arising from the conditional mean function.

Second, a literature has shown that periods exist in which long-term bond returns may forecast future stock returns and vice-versa. For instance, in a MS framework, Guidolin and Timmermann (2006) have shown that regimes may be identified in which both propositions are true, i.e. forecasting power may be derived from cross-serial correlations between stock and bond returns. However, in Section 5 we had restricted all of our models to include in the set of predictors only lagged values of the asset return to be forecasted (i.e.,

[27] To understand what the difference is, let us examine one example. If a forecaster is interested in a $h = 2$ ahead forecast, using the direct method she will estimate the model $r^j_{t+2} = \alpha^j_{dir} + \beta^j_{dir} r^j_t + \epsilon^j_{t+2}$ and use $\hat{\alpha}^j_{dir} + \hat{\beta}^j_{dir} r^j_t$ as a forecast, while using the indirect method she will estimate the model $r^j_{t+1} = \alpha^j_{ind} + \beta^j_{ind} r^j_t + \epsilon^j_{t+1}$ and then forecast as $\hat{\alpha}^j_{dir} + \hat{\beta}^j_{ind}\hat{\alpha}^j_{ind} + (\hat{\beta}^j_{ind})^2 r^j_t$.Clearly, the two methods are identical by construction at a $h = 1$ horizon.

lagged stock returns for stocks, and lagged bond returns for bonds). In the light of these literatures, this is clearly arbitrary and may omit important forecasting power, in principle capable to tilt the balance in favor or against linear vs. non-linear frameworks. As a reaction, we proceed to expand the set of variables included in X_t to include both lags of bond and stock returns, i.e., $X_t \equiv [r_t^{stock}\ r_t^{bond}\ dy_t\ \Delta i_t\ TERM_t\ \Delta s_t\ \Delta oil_t\ \pi_t\ \Delta ip_t\ \Delta u_t]'$. To avoid re-computing all forecasts and prediction errors used in Tables 2-7, we use the expanded definition of X_t in three classes of models only, i.e., linear homoskedastic, linear with GARCH(1,1)-in mean effects, and TAR, taken as a representative of the non-linear group (and giving good RMSFE performance in a few cases).

Although we refrain from reporting detailed forecast performance results, these modifications to the models originally tested in the paper seem to make little difference. For instance, looking at U.S. equity returns forecasts at a $h = 12$ horizon, the RMSFE of the autoregressive models declines from 4.39% under the direct method to 4.34% under the indirect, recursive one, while the AR-GARCH(1,1)-in mean model the RMSFE declines from 4.39% to 4.36%; in the linear homoskedastic case, the RMSFE increases from 4.54 to 4.57% without ARCH-in mean effects, and from 4.39 to 4.70% when Gaussian GARCH(1,1)-in mean effects are taken into account. Finally, the TAR (with threshold variable represented by the lagged asset returns) RMSFE increases from 4.49 to 4.65% when lagged bond returns are used among the predictors.[28] Similar conclusions hold with reference to MAFE and MPFE; as for SRs, they seem to be adversely affected by the application of iterative methods. In general, for all countries, markets, and sub-periods, changes in the performance measures implied by the addition of lagged returns on the "other" asset to the pool of prediction variables, makes little difference for the results, and approximately 50% of the experiments, it actually ends up hurting the realized (pseudo-) out-of-sample recursive performance instead of benefitting it. Therefore, it does not seem that our earlier conclusions may depend on any of the detailed choices we have made about the application of direct vs. indirect methods or on allowing for cross-asset predictability patterns, even under non-linear frameworks.

6.2. *Asymmetric Loss Functions*

In addition to the DM statistics using a square loss function, we have also conducted tests based on the DM statistic when the loss function is a linear-exponential (linex, for short) that allows for asymmetric effects of positive and negative forecast errors on the loss perceived by a forecaster, so that the difference in loss functions is defined as:

$$diff_{t,t+h}^{(\mathcal{M}_1,\mathcal{M}_2)} = \left[\exp(ae_{t,t+h}^{j,\mathcal{M}_1}) - ae_{t,t+h}^{j,\mathcal{M}_1} - 1\right] - \left[\exp(ae_{t,t+h}^{j,\mathcal{M}_2}) - ae_{t,t+h}^{j,\mathcal{M}_2} - 1\right], \tag{28}$$

where $a \neq 0$. Following Patton and Timmermann (2007), we use $a = 1$. In general, we observe test results that are qualitatively consistent with what reported in Tables 4 and 5. However, a few differences exist that deserve attention. Table 8 – with reference to two specific country/market combinations simply taken as an example

[28] These results are largely similar for other markets, other countries, and (when this matters) using $h = 1$. For instance, for U.S. stock returns at $h = 1$, the linear homoskedastic and TAR RMSFE increase from 4.22 and 4.42%, respectively, to 4.35 and 4.53%, respectively. For U.S. bond returns at $h = 12$, the RMSFE of the autoregressive models are essentially unchanged when going from direct to indirect forecast methods, in the linear homoskedastic case, the RMSFE increases from 2.16 to 2.19% without ARCH-in mean effects, and from 2.15 to 2.16% when GARCH(1,1)-in mean effects are modeled; the TAR RMSFE increases from 2.22 to 2.28% when lagged bond returns are used. Guidolin et al. (2008) discuss a few additional findings.

– illustrates these two possibilities. In Table 8 we report the same DM p-values as in Tables 4 and 5 above the main diagonal, when a simple quadratic, symmetric loss function is assumed, and the new, linex-based results below the main diagonal. The results in Tables 4 and 5 are repeated for convenience only. P-values equal to or below 0.05 are boldfaced, drawing the attention to pairs for which a DM test may signal superior predictive accuracy from one model in the pair. Panel A refers to DM tests for U.K. equity return predictions at $h = 1$, when we find rather important differences vs. panel C in Table 4: here it is clear that while under quadratic loss the DM test was capable from telling apart Markov switching models from all other models (showing they predict better), this stops being the case under an asymmetric linex loss. This means that a forecaster with loss function described by a linex parametrized by $a = 1$ may in fact be indifferent between Markov switching and the remaining models (linear or not), in spite of their superior RMSFE, MAFE, and SR performances. Panel B refers instead to forecasts of U.K. bond returns at $h = 12$: in this case the results above and below the main diagonal are essentially the same (p-values for Markov switching models only slightly increase but remain well below 0.05), and in fact a linex loss function reveals that for a few more pairs of models one could reject the null of no statistical difference in predictive performance. All in all, although the choice of a loss function is certainly crucial to the outcomes of our exercise, we find little evidence that most or all of our findings may be driven by the attention we have been implicitly paying to symmetric loss functions in our implementation of DM tests or when building Tables 2-7.

6.3. *Nested Models Correction*

It is well known that when two models are nested, configurations of the parameters of the nesting models exist such that the loss difference is zero, so that it may not apparent whether the Diebold and Mariano (1995) statistic is degenerate, divergent or bounded; in particular, it is no longer clear whether the DM statistic may actually be asymptotically normal as it is usually claimed. For tests that compare the forecasting ability of two nested models and a prediction horizon $h = 1$, McCracken (2007) introduces a t- Student-type statistic (called OOS-t) comparable to the DM statistics that applies to pairs of nested non-linear models. Because the asymptotic distributions of the OOS-t statistics under the null hypothesis (that there is no differential predictive accuracy as measured by square loss functions) are non standard, McCracken (2007) provides tables of asymptotically valid critical values computed by 5000 independent draws from the distributions.[29] We find that our results in Section 5.4 are robust to taking into account of the effects of nesting on the asymptotic distribution of the DM statistic. For instance, for U.S. and U.K. returns data we keep finding that MS and MSH models are significantly more accurate (i.e., they imply lower MSFEs) than all the models they nest (i.e., linear models, random walk, and AR(1), as well as the MS in case of MSH) with p-values generally below 1%. However, we also notice a general tendency for p-values to grow, which means that in a larger proportion of cases the null of no difference between loss functions cannot be rejected.

[29] The tables give the 99th, 95th, and 90th percentiles for the asymptotic null distribution of the OOS-t statistics, which are given by integrals of functions of Brownian motions. In fact, the number of Brownian motions is equal to the number of excess parameters in a nesting model, while the ratio between the number of out-of-sample forecasts and the number of observations used to compute the first of the recursive forecasts affects the range of integration. The functions of Brownian motions to be integrated also differ across forecasting schemes (recursive, rolling, fixed).

6.4. *Asymmetric Weighting in DF Tests*

As discussed in Section 4, van Dijk and Franses (2003) have suggested weighting schemes to compute DM-style tests in which the objective is to overweight either the left or the right tail of the empirical distribution of the values of the forecast target. This is equivalent to compute DM tests in which loss function differences in correspondence to any of the tails of the corresponding empirical distribution receives particular emphasis. In particular, the concern is that we might have reached conclusions that are influenced by the assumption that all loss differentials underlying the computation of DM ought to receive the same weight, or that (in Section 5.4) even when the tails are overweighted, this ought to be done symmetrically, contrary to much practice and intuition in applied finance, for which left tails are more important than right tails. To check the robustness of our results to this issue, we have re-computed Table 9 when instead of the weighting scheme W_{1t}, the two alternative schemes – i.e., $W_{2t} = 1 - \Phi(r_t^j)$ and $W_{3t} = \Phi(r_t^j)$ – are employed.

Also in this case, for reasons of space we cannot afford to report all the new results afresh. In general we find that both our general conclusions concerning the appropriate rankings of forecasting models across countries and assets and our particular findings based on DF tests in Table 6 hold intact when other, asymmetric weighting schemes are applied. This is comforting, because it means that even decision makers more interested in the prediction of left- (or, for some reason, right-) tail returns may depend on the results in Section 5. For instance, Table 9 reports sample results for U.S. bond returns prediction at $h = 1$ and for Canadian stock returns predictions at $h = 12$.[30] In the table, p-values above (below) the main diagonal refer to tests when the weighting function is W_{2t} (W_{3t}); as always, p-values equal to or below 0.05 are boldfaced to highlight the pairs of models for which the null of no superior predictive accuracy may be rejected. Although in both panels of Table 9 it is clear that p-values do change when moving from the upper to the lower diagonal (and additionally, they are different from the matching panels in Table 6), there is generally a high correspondence between boldfaced coefficients in each of the two parts of the panels in Table 9 and the appropriate sections of matching panels in Table 6. For instance, in the case of 1-month ahead forecast of U.S. stock returns, it is clear that MS and MSH are superior to all other models (some doubts exists for MSH when we overweight the prediction of extremely large U.S. stock returns, in the right tail). In the case of Canadian 12-month horizon bond return forecasts there is on the contrary only weak evidence in favor of any of the models tested in our paper, which is again consistent with our earlier comments.

7. Discussion: Why and How Can Non-Linear Models Work?

The results reported in Section 5 and 6 naturally raise one important question: While most of the existing literature (which includes but is not limited to the papers discussed in our Introduction) has generally expressed doubts and reported negative results on the usefulness of non-linear models in producing accurate predictive performance (see e.g., Bradley and Jansen, 2004, among many others), we have found cases and sub-sample periods in which *some* types of non-linear frameworks may actually forecast relatively well, and better than simple benchmarks often used in the applied literature. In particular, our finding that non-linear models have potential of out-performance especially for U.S. and U.K. asset returns data is intriguing.

On the one hand, it must be acknowledged that if the up-side of a thorough and systematic research design

[30] In this case, because results are generally quite similar to those in Table 6, we have randomly chosen the markets, countries, and horizons to provide an example in Table 9. Detailed results are available upon request.

such as the one we have implemented here consists of its ability to exhaust most or all the aspects at which an investigator may look at when in search of results on the comparative forecasting performance of non-linear model, its down-side is that by experimenting with alternative and competing non-linear frameworks (here of the ARCH-in mean, Markov switching, TAR and STR types) and using a relatively wide range of alternative performance measures, one is bound to find cases and sub-samples over which non-linear frameworks may produce good forecasting performances. Therefore, because we may have easily ended up employing sample periods (up to early 2007), data and especially data frequencies (monthly), variables and variable combinations (in the case of TAR and STR models) within the non-linear frameworks, that are different from the existing literature, it may be not entirely surprising our ability to report results that have been in some cases more favorable to non-linear models than what has been previously reported.

On the other hand, even discounting this inevitable down-side of an exhaustive analysis – i.e., the fact that "if one looks long enough, she will find a few cases in which non-linear modelling pays off" – cannot be used as a blanket explanation for our finding that in two specific financial markets, the U.S. and U.K., the chances for non-linearities to play a role apt to improve forecasting performance are significantly higher than in the rest of the G7 markets. In this regard, our intuition is that the differential performance of non-linear models across different countries depends on the heterogeneous pricing frameworks that may generates international stock and bond returns in the presence of incomplete financial integration, i.e., international market segmentation. If a researcher estimates simple non-linear frameworks – where "simple" means that the models are at most characterized by two regimes only (e.g., $k = 2$ in the Markov switching case, or the existence of a single threshold is imposed, as we have done in the TAR and STR cases) – their forecasting performance is likely to get worse as one moves away from the prediction of returns on portfolios that are mostly driven by global factors and towards portfolios that are driven by both global and local factors (see Bredin and Hyde, 2008). The reason for this effect is rather intuitive: a non-linear model helps forecasting asset returns if it helps identifying and predicting turning points and regime shifts in the process followed by the factors that are compounded into realized asset returns, in equilibrium. However, if many alternative factors are all priced, i.e., reflected by asset returns, and all or most factors are characterized by a different dynamics of regime shifts, then two phenomena take place. First, if a non-linear framework is too simple in the sense of imposing the presence of a low dimensionality for regimes (like $k = 2$ under MS), then the performance of such model will get increasingly poor as the number of independent, priced factors subject to regime switching dynamics grows. Second, while in principle one may want to experiment with more complicated, multi-regime models (like in Guidolin and Ono, 2006, and Bredin and Hyde, 2008), their structure quickly becomes cumbersome, the number of parameters grows, and as a result it may remain questionable whether the overall non-linear model performance may actually improve. The result may be that non-linear models may be doomed to disappointing predictive performance exactly when assets are priced by complex pricing framework in which both global and local factors are present. In our application, the presumption is that while U.S. and U.K. asset returns are likely to strongly co-move and provide cases in which essentially most of the dynamics in regimes comes from a (yet latent) global factor, in many other cases entertained a number of regional or local factors may be present that quickly turn our simple two-regime models into poor devices to capture and predict turning points. For instance, it is clear that German, French, and Italian asset returns may be heavily influenced by European (e.g., as driven by common monetary policy influences) factors, besides global ones; in the case of Japan, one may easily think of the presence of a geo-political, regional Asian factor; in the case of Canada, in spite of its geographical proximity to the U.S., it is well-known that the very structure of the Canadian economy (its dependence on exports of raw materials) may make the Canadian exposure to world business cycles rather different from (say) the exposure implicit in U.K. financial data.

To verify our intuition, we have performed a small-scale simulation experiment. Consider three asset markets, indexed by $i = 1, 2, 3$. The first market is exclusively driven by a global factor f_t^W which follows a two-state model in which both mean and variance are regime-dependent. Let the global state S_t^W be governed by a Markov chain with constant transition probabilities. A second market is not only driven by f_t^W but also by a regional factor f_t^R; also f_t^R follows a two-state Markov switching process with regime-dependent mean and variance; the corresponding Markov chain variable is S_t^R. Finally, the third market is affected both by global and regional factors, and also by a local factor f_t^L. For symmetry, let us also assume that the local factor follows a two-state Markov chain with constant probabilities, S_t^L. Formally, the model can be written as:

$$\begin{aligned} R_t^1 &= \alpha_1 + \beta_{1W} f_t^W + \epsilon_t^1 \\ R_t^2 &= \alpha_2 + \beta_{2W} f_t^W + \beta_{2R} f_t^R + \epsilon_t^2 \\ R_t^2 &= \alpha_3 + \beta_{3W} f_t^W + \beta_{3R} f_t^R + \beta_{3L} f_t^L + \epsilon_t^3, \end{aligned} \tag{29}$$

where $\boldsymbol{\epsilon}_t \equiv [\epsilon_t^1 \; \epsilon_t^2 \; \epsilon_t^3]'$ follows a white noise process. Based on our assumptions, we know that $f_t^m = \delta_{S_t^m} + \upsilon_{S_t^m} \xi_t^m$, where $m = W$, R, L, and $\boldsymbol{\xi}_t \equiv [\xi_t^W \; \xi_t^R \; \xi_t^L]'$ is also white noise and uncorrelated with $\boldsymbol{\epsilon}_t$. Additionally, the three Markov state variables S_t^W, S_t^R, and S_t^L are assumed to be independent. Therefore:

$$\begin{aligned} R_t^1 &= \mu_{S_t^W}^1 + \sigma_{S_t^W}^1 \eta_t^W \\ R_t^2 &= \mu_{S_t^W}^2 + \mu_{S_t^R}^2 + \sigma_{S_t^W} \eta_t^W + \sigma_{S_t^R} \eta_t^R \\ R_t^3 &= \mu_{S_t^W}^3 + \mu_{S_t^R}^3 + \mu_{S_t^L}^3 + \sigma_{S_t^W} \eta_t^W + \sigma_{S_t^R} \eta_t^R + \sigma_{S_t^L} \eta_t^L, \end{aligned} \tag{30}$$

where $\mu_{S_t^W}^i \equiv \alpha_i + \beta_{iW} \delta_{S_t^W}$, $\mu_{S_t^R}^i \equiv \beta_{iR} \delta_{S_t^R}$, $\mu_{S_t^L}^i \equiv \beta_{iL} \delta_{S_t^L}$, $\sigma_{S_t^W}^i \eta_t^W \equiv \beta_{iW} \upsilon_{S_t^W} \xi_t^W + \epsilon_t^i$, $\sigma_{S_t^R}^i \eta_t^R \equiv \beta_{iR} \upsilon_{S_t^R} \xi_t^R$, and $\sigma_{S_t^L}^i \eta_t^L \equiv \beta_{iL} \upsilon_{S_t^L} \xi_t^L$. (30) implies that the first market is purely driven by a global factor and therefore follows a simple two-state Markov switching model. The second market is also driven by a regional factor (called this way because this factor also affects the third market) which makes R_t^2 depend on both S_t^W and S_t^R; as a result R_t^2 may be thought as driven by a four-state Markov chain, i.e.,

$$R_t^2 = \begin{cases} \mu_{11}^2 + \mu_{21}^2 + \sigma_{11} \eta_t^W + \sigma_{21} \eta_t^R & \text{if } S_t^W = 1 \text{ and } S_t^R = 1 \\ \mu_{11}^2 + \mu_{22}^2 + \sigma_{11} \eta_t^W + \sigma_{22} \eta_t^R & \text{if } S_t^W = 1 \text{ and } S_t^R = 2 \\ \mu_{12}^2 + \mu_{21}^2 + \sigma_{12} \eta_t^W + \sigma_{21} \eta_t^R & \text{if } S_t^W = 2 \text{ and } S_t^R = 1 \\ \mu_{12}^2 + \mu_{22}^2 + \sigma_{12} \eta_t^W + \sigma_{22} \eta_t^R & \text{if } S_t^W = 2 \text{ and } S_t^R = 2 \end{cases}.$$

Finally, the third market is driven by global, regional, and local factors and it is easy to show that since S_t^W, S_t^R, and S_t^L are independent Markov chains, R_t^3 is driven by a eight-state Markov process with constant transition probabilities. Therefore the basic intuition is that (30) implies that moving from the leading, world-market towards the periphery many more factors become relevant and hence the required structure for the Markov chain describing the joint stock return process gets increasingly rich and complicated.

For concreteness, we have estimated model (30) for U.S., U.K., and Italian stock returns. The underlying assumption is that U.K. returns may proxy for a regional, European factor. We have obtained the following

ML estimates of the model, where I_t^m is an indicator variable that takes value of one if $S_t^m = 1$ and zero if $S_t^m = 2$ ($m =$ US, UK, IT):[31]

$$
\begin{aligned}
R_t^{US} &= \underset{(1.170)}{-0.717} I_t^{US} + \underset{(0.206)}{1.528}(1 - I_t^{US}) + [\underset{(1.405)}{6.523} I_t^{US} + \underset{(0.465)}{3.080}(1 - I_t^{US})]\eta_t^{US} \\
R_t^{UK} &= \underset{(1.653)}{-2.403} I_t^{US} + \underset{(0.291)}{2.083}(1 - I_t^{US}) - \underset{(1.197)}{0.045} I_t^{UK} + \underset{(0.307)}{0.625}(1 - I_t^{UK}) + [\underset{(0.925)}{4.611} I_t^{US} + \underset{(0.375)}{2.178}(1 - I_t^{US})]\eta_t^{US} + \\
&\quad + [\underset{(0.769)}{5.608} I_t^{UK} + \underset{(0.484)}{2.249}(1 - I_t^{UK})]\eta_t^{UK} \\
R_t^{IT} &= \underset{(0.770)}{-0.549} I_t^{US} + \underset{(0.136)}{0.425}(1 - I_t^{US}) + \underset{(0.102)}{0.387} I_t^{UK} + \underset{(0.262)}{0.625}(1 - I_t^{UK}) - \underset{(0.473)}{0.839} I_t^{IT} + \underset{(1.166)}{2.323}(1 - I_t^{IT}) + \\
&\quad + [\underset{(0.645)}{3.396} I_t^{US} + \underset{(0.350)}{1.603}(1 - I_t^{US})]\eta_t^{US} + [\underset{(0.736)}{1.729} I_t^{UK} + \underset{(0.194)}{0.693}(1 - I_t^{UK})]\eta_t^{UK} + \\
&\quad + [\underset{(1.475)}{5.211} I_t^{IT} + \underset{(0.857)}{9.248}(1 - I_t^{IT})]\eta_t^{IT}. \qquad (31)
\end{aligned}
$$

Clearly, the estimated system identifies a worldwide bear state in which all markets are driven down by the realization of $S_t^m = 1$, and a bull state in which the opposite happens.[32] Interestingly, U.K. mean stock returns seems to be driven more heavily by the state of the US/world market than by its own "regional" state; however, this is not true for Italian stock returns that are instead mostly driven by a local, Italian state factor. As one would expect in the light of the existing literature, bear states are considerably more volatile than bull states.

At this point, we have simulated 1,000 3×1 times series of returns from the estimated model (31). Each time series is 336-observation long, the same length of the monthly data set analyzed in our paper. In our simulation, the system (31) is initialized at the ergodic state probabilities for bull and bear states. In correspondence to each simulation, we have then performed a brief version of the investigation undertaken in our paper, i.e., we have recursively estimated three types of models starting from observation number 192 and computed recursive, 1-step ahead forecasts for a total of 144 predictions. From these predictions we have then computed the realized RMSFE, MAFE, and the variance of the forecast errors. The three models are: (i) a simple (as we shall see, possibly too simple) two-state MSIH model; (ii) the random walk (recursive sample mean of returns) model in (11); (iii) the AR model in (12). We then take the MSIH forecast performance as a benchmark and compute the distribution over the 1,000 simulation trials of the ratios between RMSFE, MAFE, and forecast error variance of the random walk and the autoregressive model over the MSIH measures. Clearly, if the non-linear framework outperforms the simple benchmarks, then we would expect the RMSFE, MAFE, and prediction variance ratio to be all below 1 (at least over the average of the simulations).

For each of the three stock markets, Figure 2 reports histograms of the simulated results, along with the average and median of each ratio. We also compute the percentage of the 1,000 simulations in which it happens that the two-state Markov switching model outperforms the random walk. Guidolin et al. (2008) also plot histograms for ratios obtained when the benchmarks is the AR(1) model, although results are practically indistinguishable. Results for simulated U.S. stock returns are overwhelmingly favorable to the non-linear model. Of course, this is not a complete surprise as results have been built assuming that a two-state Markov switching model would govern R_t^{US}. Yet, it is comforting to see that in simulated recursive, out-of-sample

[31] The estimated transition probabilities are $\hat{p}_{11}^{US} = 0.8481$, $\hat{p}_{22}^{US} = 0.9629$; $\hat{p}_{11}^{UK} = 0.8860$, $\hat{p}_{22}^{UK} = 0.8448$; $\hat{p}_{11}^{IT} = 0.9536$, $\hat{p}_{22}^{IT} = 0.8698$. In (31) standard errors are in parenthesis.

[32] The only exception is represented by $S_t^{UK} = 1$ that actually implies higher returns on the Italian stock market.

experiments similar to the ones performed in the paper on actual data, the non-linear framework outperforms the benchmarks both on average (e.g., the average relative RMSFE of the random walk vs. MSIH is 1.018 and the same average of the AR(1) vs. MSIH is 1.015) and especially in terms of percentage of simulation in which it gives a higher predictive accuracy than the benchmarks do (99.6 and 96.9 percent, vs. the random walk and AR(1), respectively). Results for MAFE performance are largely similar. However, the figures show that results turn mixed when we examine the relative forecasting performance of the two-state Markov switching fitted to simulated U.K. stock returns. For instance, when compared to the random walk, the mean relative RMSFE is 0.99 while only in 43.7% of the simulations the non-linear model outperforms the no-predictability benchmark. Our intuition is that – although a non-linear framework would be called for – the simple, "off-the-shelf" two-state Markov switching model we have used in this experiment as well as in the paper may already turn too rough and simple to outperform simpler, parsimonious single-state benchmarks. In fact, we know that by construction in our experiment a four-state Markov switching model would be required, while we have simply fitted and employed a two-state one. Once more, results of comparisons to the AR(1) model in Figure 3 or performance measurement based on MAFE give identical result. Finally, the picture is completely opposite in the case of simulated Italian returns. For instance, when compared to the AR(1) model, the mean relative RMSFE is 0.956 and in only 0.1% of the simulations the MSIH gives a better RMSFE than the AR(1). Results are similar when comparisons are made on the basis of MAFE and relative to the random walk. Of course, this completely fits our conjecture: Italian stock returns are generated by a very complicated non-linear model in which in principle eight different regimes ought to be specified and estimated; as a result a basic two-regime model ends up losing to even the naivest of the prediction benchmarks.[33]

All in all, the message seems to be that even discounting a widespread need to capture non-linearities, the precise structure (in our example, as represented by the number of regimes) of the non-linear model always plays a key role. Such a role may be so pervasive that in principle it may better – at lest as far as the forecasting performance goes – to use a rudimental, naive forecasting tool than selecting a generally useful non-linear framework that may be plagued by gross misspecifications. Our empirical results in Sections 4 and 5 end up suggesting that while simple two-regime MS, TAR, and STAR model may frequently be sufficiently close to "correct specification" to provide an accurate prediction tool in the case of the Anglo-Saxon financial markets, this is unlikely to be the case for continental European and Asian markets, which are probably more prone to regional and local effects in the way assets are priced. Whether richer and more complicated non-linear frameworks of any of the types examined in this paper (e.g., Bredin and Hyde's, 2008, multiple regime STR models) may eventually provide competitive forecasting performance remains an open question.

8. **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. 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 for most combinations of horizons, countries, and markets, it turns

[33]We also investigate the relative variance of forecast errors across models. In general, the ability of the two-state MS model to lead to the lowest forecast variance mirrors the results reported for the RMSFE.

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 simpler benchmarks may deliver accurate predictive performance.

Three additional results emerge. First, U.S. and U.K. asset return data 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, even though it does not seem that the role for non-linear models we have detected depends on any particular part of our sample, at least for five out of seven of the countries examined, we have uncovered that the more turbulent 1999-2002 period implies a lower amount of predictability (both in terms of RMSFEs and of success ratios) than the remaining two periods; in this sub-intervals, it tends to happen more frequently than otherwise that the simpler benchmarks that minimize the need of estimation of parameters and that refrain from committing to specific forms of non-linearities may have been slightly more successful than more complicated and generously parameterized models. Third, U.S. and U.K. data appear once more “special” because they are the only two countries in which the data allow us to find statistically significant difference between forecasting models. Although this third finding is completely consistent with a recent literature that has used non-linear models to capture the dynamics of and forecast financial returns in the U.S. and the U.K. (see e.g., Guidolin and Timmermann, 2006, Guidolin and Ono, 2006, Lekko and Milas, 2004, and McMillan, 2003), it remains to be clarified – for instance, using micro-structural models that describe the price adjustment dynamics in Anglo-Saxon vs. other G7 countries, or macro-finance models that might illustrate and different connection among financial returns and underlying macroeconomic factors – the reasons underlying these systematic differences in results. Section 7 has moved a few steps in this direction and connected the global/regional/local features of the underlying linear factor representation to the chances that relatively stylized non-linear models may produce a satisfactory performance. However, what we have presented is just an example and much more work seems to be justified to explore these aspects.

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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 prod. growth	0.1713	0.1379	1.3806	0.3292	5.2442	76.578**	33.773**	19.289**
Δ log eff. 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 prod. growth	0.0530	0.0893	2.7120	-0.0950	3.8269	10.079**	203.58**	21.337**
Δ log eff. 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 prod. growth	0.1290	0.1656	1.4269	-0.1413	5.3489	78.360**	80.077**	57.528**
Δ log eff. 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 prod. growth	0.1285	0.0035	2.6669	0.5201	5.2122	83.657**	82.829**	21.6414**
Δ log eff. 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 prod. growth	0.1647	0.1283	1.6197	0.0169	3.0172	0.0201	104.82**	10.214*
Δ log eff. 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 prod. growth	0.9869	1.4647	12.0630	-0.3860	4.1650	27.348**	16.913**	19.932**
Δ log eff. exchange rate	0.0134	0.0370	1.6592	-0.3874	5.4494	92.396**	31.939**	23.009**
Δ unemployment rate	0.0033	0.0000	0.1196	0.6786	4.5150	57.918**	428.92**	176.67**
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 prod. growth	0.2019	0.2263	0.6501	-0.4226	3.8477	20.062**	48.005**	15.413**
Δ log eff. 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

Panel A

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

Table 2 [Cont.]

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

Panel B

		Japan		Germany	
		Stocks	Bonds	Stocks	Bonds
RMSFE	h=1	1. Logistic STAR - T-bill	1. RW w/drift & GARCH(1,1)-in mean	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. RW w/drift & GARCH(1,1)-in mean	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. RW w/drift & TARCH(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. RW w/drift & 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. RW w/drift & GARCH(1,1)-in mean	1. RW w/drift & TARCH(1,1)-in mean	1. RW w/drift & GARCH(1,1)-in mean	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. RW w/drift & t-GARCH(1,1)-in mean	3. RW w/drift & t-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. RW w/drift & t-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. RW w/drift & GARCH(1,1)-in mean	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. RW w/drift & TARCH(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. RW w/drift & GARCH(1,1)-in mean	1. RW w/drift & TARCH(1,1)-in mean	1. Logistic STAR-GARCH(1,1)
		2. MSH	2. AR(1) with GARCH(1,1)	2. RW w/drift & t-EGARCH(1,1)-in mean	2. AR(1)
		3. AR(1)	3. Random walk with drift	3. RW w/drift & GARCH(1,1)-in mean	3. AR(1) with GARCH(1,1)
	h=12	1. Logistic STAR - T-bill	1. RW w/drift & GARCH(1,1)-in mean	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. RW w/drift & 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. RW w/drift & t-EGARCH(1,1)-in mean	1. Exponential STAR - T-bill	1. Logistic STAR - T-bill
		2. RW w/drift & t-TARCH(1,1)-in mean	2. TAR-SR	2. RW w/drift & EGARCH(1,1)-in mean	2. MSH
		3. RW w/drift & 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. RW w/drift & 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. RW w/drift & GARCH(1,1)-in mean	3. Linear homoskedastic
	h=12	1. RW w/drift & 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

Panel C

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

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

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

Table 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

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

Table 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

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

Table 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

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

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

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

Table 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

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

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**

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

Table 4

Diebold-Mariano 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	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

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	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

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	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

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	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

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	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

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 States Bond 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	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		0.489	0.481	0.373	0.240	0.199	0.854	0.593	0.409	0.660	0.990	1.000	0.975	0.872	0.945	0.993	0.978	0.984	0.189	**0.000**
Random walk (with drift)	0.211		**0.000**	0.161	**0.012**	0.418	0.569	0.523	0.492	0.548	0.655	0.996	0.964	0.889	0.896	0.975	0.984	0.929	0.175	**0.013**
AR(1)	0.162	1.000		0.179	**0.014**	0.422	0.578	0.531	0.499	0.558	0.664	0.997	0.968	0.892	0.906	0.978	0.987	0.934	0.178	**0.014**
Random walk (with drift and GARCH(1,1))	0.246	0.618	0.603		0.058	0.546	0.681	0.635	0.607	0.669	0.752	0.997	0.965	0.894	0.919	0.985	0.985	0.932	0.217	**0.016**
AR(1) with GARCH(1,1)	0.250	0.201	0.205	0.178		0.703	0.801	0.770	0.746	0.799	0.854	0.999	0.983	0.924	0.971	0.997	0.997	0.976	0.330	**0.034**
GARCH(1,1) in mean and exogenous predictors	0.105	0.410	0.391	0.317	0.396		0.875	0.810	0.753	0.930	0.974	1.000	0.974	0.884	0.946	0.989	0.979	0.993	0.239	**0.002**
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.540	0.262	0.163	0.206	0.227	0.142		0.318	0.179	0.403	1.000	1.000	0.962	0.850	0.911	0.984	0.961	0.980	0.155	**0.000**
EGARCH(1,1)-in mean and exogenous predictors	0.086	0.275	0.249	0.273	0.268	0.435	0.710		0.306	0.572	0.958	1.000	0.971	0.868	0.947	0.993	0.978	0.987	0.182	**0.000**
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.423	0.223	0.082	0.251	0.121	0.602	0.599	**0.034**		0.671	0.995	1.000	0.970	0.869	0.949	0.992	0.978	0.988	0.201	**0.000**
TGARCH(1,1)-in mean and exogenous predictors	0.176	0.402	0.385	0.371	0.347	0.078	0.466	0.060	0.374		0.840	0.999	0.965	0.862	0.909	0.982	0.967	0.958	0.182	**0.001**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.072	0.275	0.238	0.158	0.244	0.336	0.099	0.318	0.233	0.476		1.000	0.952	0.830	0.896	0.982	0.955	0.963	0.122	**0.000**
Exponential STAR - T-bill	0.154	0.240	0.230	0.231	0.176	0.167	0.181	0.144	0.157	0.178	0.172		0.181	0.174	**0.000**	**0.000**	**0.000**	**0.005**	**0.003**	**0.000**
Exponential STAR-SRF	0.235	0.307	0.301	0.291	0.260	0.252	0.217	0.255	0.244	0.261	0.237	0.472		0.226	0.068	0.182	**0.000**	0.162	**0.039**	**0.004**
Logistic STAR - T-bill	0.097	0.306	0.313	0.432	0.476	0.261	0.192	0.176	0.267	0.064	**0.002**	0.674	0.611		0.293	0.424	0.551	0.306	0.112	**0.036**
Logistic STAR-SRF	0.362	0.394	0.378	0.342	0.323	0.381	0.284	0.387	0.373	0.419	0.393	0.058	0.823	0.107		0.978	1.000	0.529	0.062	**0.001**
TAR-SR	0.231	0.317	0.306	0.283	0.199	0.255	0.258	0.232	0.237	0.291	0.274	0.064	0.683	0.097	0.156		0.993	0.244	**0.018**	**0.000**
TAR-SRF	0.297	0.299	0.283	0.287	0.210	0.289	0.306	0.294	0.298	0.321	0.330	**0.039**	1.000	1.000	0.054	0.243		0.093	**0.019**	**0.001**
Logistic STAR-GARCH(1,1)	0.307	0.434	0.436	0.315	0.292	0.270	0.291	0.294	0.294	0.401	0.386	0.243	0.653	0.874	0.824	0.771	**0.000**		**0.034**	**0.000**
MS Two-state homoskedastic	0.294	0.597	0.660	0.622	0.907	0.385	0.288	0.270	0.258	0.406	0.397	0.126	0.299	0.538	0.367	0.259	0.287	0.349		**0.016**
MS Two-state heteroskedastic	0.121	0.230	0.243	0.241	0.333	0.163	0.097	0.138	0.124	0.148	0.100	0.101	0.173	0.278	0.173	0.124	0.165	0.144	0.227	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

Table 5 [Cont.]

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

Panel C: 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	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		0.212	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	

Panel D: 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	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		0.083	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	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

Table 5 [Cont.]

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

Panel E: 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**	

Panel F: 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	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

Table 5 [Cont.]

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

Panel G: 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	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		0.059	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	

Panel H: Italian 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	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		0.801	0.338	0.494	0.648	0.956	0.274	0.949	0.770	0.982	0.371	0.975	0.165	0.923	0.841	0.904	0.898	0.371	0.916	0.994
Random walk (with drift)	0.700		0.075	**0.038**	0.397	0.727	0.119	0.804	0.486	0.832	0.095	0.780	0.133	0.716	0.658	0.640	0.874	0.192	0.738	0.946
AR(1)	0.094	0.367		0.667	0.806	0.926	0.522	0.956	0.896	0.967	0.604	0.987	0.510	0.980	0.912	0.949	0.903	0.653	0.926	0.991
Random walk (with drift and GARCH(1,1))	0.985	0.195	0.691		0.648	0.899	0.369	0.937	0.797	0.958	0.383	0.922	0.388	0.894	0.832	0.823	0.893	0.495	0.904	0.984
AR(1) with GARCH(1,1)	0.330	0.243	0.669	0.554		0.824	0.226	0.891	0.640	0.881	0.256	0.913	0.307	0.868	0.769	0.815	0.908	0.342	0.799	0.984
GARCH(1,1) in mean and exogenous predictors	0.243	0.090	0.150	0.183	0.151		**0.037**	0.632	0.256	0.763	0.061	0.586	**0.038**	0.479	0.461	0.403	0.870	**0.041**	0.539	0.933
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.650	0.499	0.295	0.948	0.537	0.123		0.982	0.927	0.987	0.629	0.988	0.495	0.965	0.887	0.949	0.905	0.715	0.937	0.996
EGARCH(1,1)-in mean and exogenous predictors	1.000	0.649	0.240	0.330	0.075	0.915	**0.033**		0.074	0.496	**0.028**	0.477	0.056	0.383	0.377	0.325	0.848	**0.046**	0.438	0.935
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.803	0.977	0.095	0.712	0.079	0.134	**0.000**	0.093		0.834	0.080	0.827	0.206	0.757	0.692	0.669	0.882	0.215	0.770	0.988
TGARCH(1,1)-in mean and exogenous predictors	0.134	0.097	0.201	0.183	0.232	0.206	0.106	0.878	0.282		**0.022**	0.476	**0.016**	0.370	0.373	0.302	0.851	**0.018**	0.437	0.880
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.672	0.374	0.773	0.692	0.515	0.077	0.700	0.166	1.000	0.143		0.976	0.448	0.956	0.880	0.918	0.900	0.617	0.929	0.993
Exponential STAR - T-bill	0.109	0.730	0.084	0.318	**0.000**	0.979	0.071	0.489	0.225	0.996	0.130		**0.025**	0.292	0.352	0.195	0.851	**0.023**	0.454	0.899
Exponential STAR-SRF	0.581	0.502	0.993	0.832	0.335	0.193	0.840	0.390	0.742	0.123	0.894	0.097		0.920	0.850	0.919	0.898	0.786	0.928	0.995
Logistic STAR - T-bill	0.286	0.862	0.059	0.375	1.000	0.146	**0.048**	0.608	0.180	0.576	0.159	0.610	0.377		0.466	0.366	0.859	0.074	0.557	0.906
Logistic STAR-SRF	0.513	0.297	0.339	0.640	1.000	0.100	0.492	0.695	1.000	0.124	0.491	0.860	0.492	0.885		0.453	0.853	0.152	0.583	0.907
TAR-SR	0.419	0.398	0.198	0.632	0.737	0.687	0.221	0.284	1.000	0.602	0.202	0.266	0.423	0.225	0.703		0.877	0.095	0.606	0.913
TAR-SRF	**0.002**	0.526	0.084	0.251	0.363	0.536	**0.045**	0.581	0.387	0.528	0.151	0.617	1.000	0.562	0.556	0.527		0.101	0.156	0.206
Logistic STAR-GARCH(1,1)	1.000	0.686	0.132	0.984	0.337	0.233	0.661	**0.000**	0.775	0.131	0.632	0.097	0.635	0.263	0.503	0.431	**0.022**		0.925	0.995
MS Two-state homoskedastic	0.113	0.817	0.193	0.358	0.577	0.676	0.207	0.427	0.612	0.598	0.256	0.167	0.088	0.946	0.486	0.781	0.583	0.103		0.975
MS Two-state heteroskedastic	**0.046**	0.258	**0.043**	0.118	**0.028**	0.269	**0.026**	0.253	0.079	0.505	**0.036**	0.364	0.054	0.261	0.143	0.259	0.414	**0.040**	0.167	

Note: The table presents p-values for Diebold and Mariano's (1995, DM) and Giacomini-White's (2006, GW) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above the main diagonal we report DM p-values; below the main diagonal, in each cell we show GW p-values.

Table 6

Van Dijk-Franses Equal Predictive Accuracy Tests (One-Sided)

Panel A: United States, 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		0.673	0.718	0.648	0.642	0.275	0.877	0.154	0.820	0.060	0.882	0.718	0.346	0.569	0.164	0.751	0.894	0.741	**0.001**	**0.002**
Random walk (with drift)	0.106		0.645	0.286	0.364	0.287	0.727	0.112	0.650	0.066	0.736	0.645	0.327	0.409	0.327	0.663	0.888	0.525	**0.000**	**0.001**
AR(1)	0.071	0.178		0.182	0.174	0.255	0.715	0.094	0.631	0.051	0.727	0.500	0.282	0.383	0.282	0.653	0.888	0.503	**0.000**	**0.001**
Random walk (with drift and GARCH(1,1))	0.098	0.433	0.739		0.443	0.299	0.742	0.130	0.673	0.065	0.751	0.818	0.352	0.434	0.352	0.674	0.889	0.558	**0.000**	**0.001**
AR(1) with GARCH(1,1)	0.066	0.205	0.502	0.208		0.296	0.745	0.139	0.681	0.054	0.755	0.826	0.358	0.443	0.358	0.676	0.890	0.577	**0.000**	**0.000**
GARCH(1,1) in mean and exogenous predictors	0.333	0.926	0.959	0.936	0.965		0.860	0.314	0.826	0.063	0.865	0.745	0.725	0.695	0.725	0.778	0.898	0.864	**0.002**	**0.003**
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.508	0.933	0.961	0.937	0.963	0.832		**0.047**	0.276	0.057	0.647	0.285	0.123	0.113	0.123	0.540	0.882	0.320	**0.002**	**0.004**
EGARCH(1,1)-in mean and exogenous predictors	0.802	0.949	0.972	0.951	0.972	0.877	0.817		0.947	0.142	0.940	0.906	0.846	0.881	0.846	0.838	0.901	0.866	**0.007**	**0.008**
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.710	0.959	0.980	0.955	0.977	0.855	0.789	0.487		**0.047**	0.728	0.369	0.180	0.178	0.180	0.655	0.886	0.399	**0.001**	**0.002**
TGARCH(1,1)-in mean and exogenous predictors	0.847	0.963	0.980	0.968	0.983	0.986	0.927	0.483	0.504		0.937	0.949	0.940	0.933	0.940	0.884	0.909	0.978	**0.010**	**0.008**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.588	0.937	0.964	0.937	0.963	0.780	0.652	0.196	0.243	0.180		0.273	0.117	0.109	0.118	0.509	0.881	0.304	**0.002**	**0.004**
Exponential STAR - T-bill	0.071	0.178	0.500	0.261	0.498	**0.041**	**0.039**	**0.028**	**0.020**	**0.020**	**0.036**		0.181	0.166	0.181	0.453	0.876	0.307	**0.002**	**0.004**
Exponential STAR-SRF	0.636	0.953	0.969	0.951	0.967	0.749	0.675	0.524	0.537	0.532	0.632	0.194		0.570	0.652	0.751	0.894	0.741	**0.001**	**0.002**
Logistic STAR - T-bill	0.930	0.938	0.958	0.939	0.958	0.920	0.913	0.866	0.847	0.855	0.899	0.578	0.770		0.431	0.774	0.893	0.614	**0.003**	**0.004**
Logistic STAR-SRF	**0.021**	0.738	0.812	0.745	0.811	0.113	**0.027**	**0.015**	**0.016**	**0.008**	**0.008**	0.084	0.148	**0.028**		0.751	0.894	0.741	**0.001**	**0.002**
TAR-SR	0.981	0.963	0.975	0.969	0.979	0.963	0.926	0.772	0.695	0.802	0.875	0.381	0.592	0.218	0.991		0.878	0.360	**0.007**	**0.010**
TAR-SRF	0.703	0.909	0.933	0.912	0.934	0.780	0.718	0.518	0.531	0.527	0.664	0.278	0.487	0.139	0.947	0.345		0.110	0.058	0.056
Logistic STAR-GARCH(1,1)	0.384	0.804	0.843	0.811	0.845	0.444	0.373	0.294	0.265	0.274	0.347	0.128	0.299	0.146	0.706	0.219	0.247		**0.000**	**0.000**
MS Two-state homoskedastic	**0.003**	**0.006**	**0.007**	**0.003**	**0.003**	**0.001**	**0.002**	**0.002**	**0.002**	**0.001**	**0.002**	**0.002**	**0.002**	**0.004**	**0.010**	**0.001**	**0.004**	**0.006**		0.286
MS Two-state heteroskedastic	**0.002**	**0.001**	**0.001**	**0.001**	**0.000**	**0.001**	**0.001**	**0.001**	**0.001**	**0.000**	**0.001**	**0.001**	**0.001**	**0.003**	**0.006**	**0.001**	**0.003**	**0.004**	**0.031**	

Panel B: United States, 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		0.058	0.081	**0.039**	**0.043**	0.221	0.391	0.656	0.824	0.345	0.740	0.050	**0.014**	**0.010**	**0.014**	0.275	0.868	**0.045**	**0.002**	**0.002**
Random walk (with drift)	0.898		0.876	0.237	0.653	0.933	0.978	0.982	0.965	0.866	0.972	0.103	0.188	**0.000**	0.187	0.617	0.878	0.427	**0.007**	**0.011**
AR(1)	0.896	**0.000**		0.064	0.178	0.908	0.980	0.950	0.950	0.832	0.976	0.096	0.091	**0.010**	0.091	0.515	0.878	0.331	**0.006**	**0.009**
Random walk (with drift and GARCH(1,1))	0.729	0.059	0.076		0.798	0.960	0.988	0.975	0.971	0.898	0.980	0.696	0.205	**0.005**	0.204	0.632	0.880	0.449	**0.006**	**0.009**
AR(1) with GARCH(1,1)	0.630	**0.013**	**0.021**	0.072		0.963	0.992	0.937	0.964	0.893	0.982	0.294	0.124	0.065	0.123	0.558	0.880	0.367	**0.004**	**0.007**
GARCH(1,1) in mean and exogenous predictors	0.113	0.054	0.051	0.182	0.267		0.540	0.690	0.851	0.473	0.802	0.057	**0.009**	**0.007**	**0.009**	0.303	0.870	**0.036**	**0.001**	**0.002**
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.088	0.068	0.068	0.183	0.267	0.435		0.731	0.856	0.454	0.936	**0.018**	**0.000**	**0.000**	**0.000**	0.261	0.869	0.057	**0.003**	**0.004**
EGARCH(1,1)-in mean and exogenous predictors	0.277	0.068	0.066	0.213	0.305	0.651	0.635		0.686	0.336	0.426	**0.019**	**0.016**	**0.006**	**0.016**	**0.021**	0.856	0.110	**0.009**	**0.012**
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.130	**0.050**	**0.050**	0.165	0.249	0.409	0.507	0.193		0.157	0.233	**0.033**	**0.032**	**0.020**	**0.032**	0.131	0.844	0.071	**0.001**	**0.002**
TGARCH(1,1)-in mean and exogenous predictors	0.822	0.122	0.120	0.307	0.416	1.000	0.963	0.885	0.988		0.804	0.123	**0.027**	**0.032**	**0.027**	0.331	0.874	0.059	**0.002**	**0.003**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.640	0.132	0.133	0.300	0.398	0.981	0.972	0.816	0.994	0.346		**0.025**	**0.001**	**0.000**	**0.001**	0.184	0.867	**0.041**	**0.004**	**0.005**
Exponential STAR - T-bill	0.867	**0.004**	**0.000**	0.856	0.967	0.928	0.912	0.913	0.936	0.839	0.833		**0.038**	**0.007**	**0.037**	0.553	0.878	0.309	**0.009**	**0.011**
Exponential STAR-SRF	0.954	0.883	0.891	0.933	0.964	0.965	0.955	0.970	0.973	0.943	0.947	**0.003**		0.569	0.093	0.770	0.888	0.675	**0.015**	**0.018**
Logistic STAR - T-bill	0.890	0.763	0.770	0.834	0.881	0.913	0.899	0.915	0.918	0.869	0.866	**0.028**	0.186		0.427	0.793	0.885	0.621	**0.017**	**0.021**
Logistic STAR-SRF	0.931	0.857	0.866	0.908	0.944	0.947	0.934	0.953	0.955	0.919	0.923	**0.005**	0.432	0.842		0.770	0.888	0.676	**0.015**	**0.018**
TAR-SR	0.966	0.931	0.937	0.959	0.979	0.975	0.966	0.980	0.980	0.958	0.959	**0.023**	0.694	0.965	0.826		0.865	0.374	**0.033**	**0.037**
TAR-SRF	0.911	0.861	0.869	0.902	0.932	0.925	0.914	0.930	0.932	0.901	0.902	**0.001**	0.766	0.906	0.904	0.688		0.116	0.081	0.081
Logistic STAR-GARCH(1,1)	0.919	0.674	0.684	0.805	0.877	0.964	0.937	0.966	0.969	0.906	0.923	**0.001**	0.149	0.398	0.146	0.089	0.111		**0.003**	**0.003**
MS Two-state homoskedastic	0.212	0.062	0.062	0.081	0.109	0.261	0.258	0.241	0.259	0.192	0.190	**0.006**	**0.037**	0.097	0.052	**0.034**	0.066	0.069		0.583
MS Two-state heteroskedastic	**0.005**	**0.002**	**0.002**	**0.001**	**0.003**	**0.008**	**0.005**	**0.006**	**0.005**	**0.004**	**0.002**	**0.000**	**0.001**	**0.012**	**0.004**	**0.002**	**0.010**	**0.002**	**0.000**	

Note: The table presents p-values for van Dijk and Franses (2003, DF) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in the cells above the main diagonal we report DF p-values for stock return forecasts; below the main diagonal, in each cell we show DF p-values for bond return forecasts.

Table 6 [Cont.]

Van Dijk-Franses Equal Predictive Accuracy Tests (One-Sided)

Panel C: United Kingdom, 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		0.999	0.999	0.999	0.998	0.989	0.968	0.939	0.982	0.990	0.935	0.999	0.333	0.291	0.211	0.986	0.633	0.957	**0.001**	0.069
Random walk (with drift)	0.579		0.523	0.159	0.510	**0.042**	**0.002**	**0.012**	**0.028**	0.111	**0.002**	0.523	**0.001**	**0.013**	**0.002**	**0.003**	**0.018**	**0.002**	**0.000**	**0.005**
AR(1)	0.550	0.419		0.292	0.497	**0.039**	**0.003**	**0.013**	**0.030**	0.118	**0.002**	0.500	**0.001**	**0.012**	**0.001**	**0.002**	**0.015**	**0.001**	**0.000**	**0.004**
Random walk (with drift and GARCH(1,1))	0.620	0.780	0.644		0.707	**0.046**	**0.003**	**0.016**	**0.040**	0.122	**0.003**	0.708	**0.001**	**0.016**	**0.002**	**0.003**	**0.021**	**0.003**	**0.000**	**0.006**
AR(1) with GARCH(1,1)	0.703	0.579	0.906	0.522		**0.044**	**0.003**	**0.013**	**0.034**	0.100	**0.003**	0.503	**0.001**	**0.017**	**0.002**	**0.003**	**0.021**	**0.004**	**0.000**	**0.006**
GARCH(1,1) in mean and exogenous predictors	0.687	0.476	0.541	0.431	0.371		0.641	0.586	0.778	0.865	0.482	0.961	0.062	0.145	**0.006**	0.364	0.145	0.194	**0.000**	**0.019**
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.386	0.384	0.402	0.336	0.231	0.133		0.427	0.885	0.924	0.219	0.997	**0.036**	0.107	**0.037**	0.156	0.161	0.131	**0.002**	**0.041**
EGARCH(1,1)-in mean and exogenous predictors	0.382	0.367	0.379	0.321	0.218	0.088	0.434		0.899	0.911	0.282	0.987	0.051	0.104	0.069	0.303	0.195	0.184	**0.003**	0.050
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.213	0.308	0.287	0.262	0.145	0.061	0.138	0.240		0.652	**0.014**	0.970	**0.016**	**0.045**	**0.025**	0.108	0.097	**0.049**	**0.001**	**0.026**
TGARCH(1,1)-in mean and exogenous predictors	0.570	0.435	0.479	0.390	0.314	0.121	0.712	0.811	0.878		**0.016**	0.882	**0.007**	0.076	**0.012**	**0.033**	0.087	**0.046**	**0.002**	**0.021**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.193	0.314	0.303	0.267	0.156	**0.032**	0.119	0.268	0.534	0.080		0.998	**0.039**	0.121	0.074	0.407	0.236	0.239	**0.003**	**0.048**
Exponential STAR - T-bill	0.550	0.419	0.500	0.356	0.094	0.459	0.598	0.621	0.713	0.521	0.697		0.559	0.401	0.751	0.931	0.900	0.937	**0.000**	0.099
Exponential STAR-SRF	0.363	0.400	0.420	0.360	0.283	0.199	0.495	0.554	0.732	0.297	0.751	0.151		0.368	0.611	0.931	0.684	0.837	**0.015**	0.170
Logistic STAR - T-bill	0.546	0.456	0.491	0.426	0.389	0.441	0.583	0.631	0.709	0.509	0.700	0.300	0.616		0.678	0.827	0.770	0.836	0.086	0.294
Logistic STAR-SRF	0.363	0.400	0.420	0.360	0.283	0.199	0.495	0.554	0.732	0.297	0.751	0.151	0.251	0.384		0.988	0.702	0.937	**0.001**	0.076
TAR-SR	0.884	0.633	0.704	0.612	0.632	0.805	0.875	0.882	0.910	0.860	0.925	0.615	0.937	0.828	0.937		0.231	0.275	**0.001**	**0.036**
TAR-SRF	0.216	0.227	0.220	0.189	0.126	0.135	0.222	0.229	0.320	0.180	0.315	0.148	0.238	0.223	0.238	0.082		0.690	**0.000**	**0.034**
Logistic STAR-GARCH(1,1)	0.392	0.398	0.417	0.357	0.268	0.148	0.501	0.571	0.762	0.250	0.784	0.162	0.514	0.388	0.514	0.063	0.771		**0.000**	**0.027**
MS Two-state homoskedastic	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.002**	**0.001**	**0.001**	**0.001**	**0.001**		0.914
MS Two-state heteroskedastic	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.001**	**0.002**	**0.001**	**0.001**	**0.001**	**0.001**	0.503	

Panel D: Japan, 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		0.621	0.457	0.739	0.540	0.832	0.936	0.277	0.882	0.417	0.580	0.457	0.820	0.242	0.840	0.844	0.804	0.614	0.257	0.270
Random walk (with drift)	0.220		0.058	0.904	0.330	0.672	0.835	0.263	0.735	0.354	0.445	0.058	0.724	0.171	0.711	0.715	0.645	0.519	0.205	0.216
AR(1)	0.213	0.557		0.962	0.749	0.815	0.902	0.354	0.808	0.469	0.598	0.500	0.812	0.219	0.796	0.781	0.730	0.624	0.268	0.290
Random walk (with drift and GARCH(1,1))	0.290	0.984	0.968		0.063	0.500	0.729	0.200	0.641	0.263	0.315	**0.038**	0.589	0.123	0.591	0.631	0.539	0.397	0.144	0.148
AR(1) with GARCH(1,1)	0.214	0.383	0.336	**0.039**		0.750	0.857	0.311	0.759	0.409	0.515	0.251	0.752	0.192	0.739	0.737	0.675	0.572	0.213	0.233
GARCH(1,1) in mean and exogenous predictors	0.709	0.891	0.901	0.830	0.888		0.849	0.078	0.699	0.113	0.129	0.185	0.622	0.142	0.641	0.647	0.557	0.346	0.103	0.102
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.453	0.957	0.975	0.890	0.944	0.304		**0.002**	0.441	**0.004**	**0.016**	0.098	0.262	0.086	0.273	0.469	0.233	0.189	0.051	0.050
EGARCH(1,1)-in mean and exogenous predictors	0.378	0.807	0.817	0.659	0.817	0.283	0.288		0.976	0.900	0.916	0.646	0.910	0.298	0.934	0.860	0.890	0.730	0.403	0.430
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.869	0.869	0.869	0.869	0.869	0.869	0.869	0.869		0.051	0.116	0.192	0.388	0.162	0.385	0.501	0.328	0.294	0.102	0.107
TGARCH(1,1)-in mean and exogenous predictors	0.134	0.669	0.675	0.566	0.680	0.061	0.296	0.472	0.130		0.837	0.531	0.851	0.256	0.884	0.813	0.824	0.652	0.293	0.313
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.617	0.928	0.940	0.888	0.941	0.500	0.704	0.744	0.131	0.857		0.402	0.803	0.209	0.829	0.767	0.738	0.569	0.206	0.216
Exponential STAR - T-bill	0.145	**0.003**	**0.001**	**0.003**	**0.043**	0.054	**0.012**	0.087	0.130	0.213	**0.031**		0.488	0.163	0.502	0.605	0.464	0.352	0.140	0.144
Exponential STAR-SRF	0.135	0.259	0.259	0.195	0.290	0.055	0.097	0.180	0.130	0.204	0.105	0.095		0.090	0.541	0.585	0.460	0.288	0.135	0.125
Logistic STAR - T-bill	0.716	0.865	0.863	0.849	0.863	0.712	0.792	0.864	0.133	0.785	0.730	0.081	0.887		0.879	0.797	0.830	0.830	0.665	0.676
Logistic STAR-SRF	0.691	0.881	0.879	0.862	0.879	0.678	0.782	0.914	0.133	0.786	0.707	0.093	0.892	0.232		0.581	0.432	0.282	0.131	0.119
TAR-SR	0.735	0.885	0.882	0.870	0.883	0.728	0.811	0.912	0.133	0.810	0.757	0.069	0.885	0.599	0.796		0.371	0.324	0.138	0.143
TAR-SRF	0.634	0.830	0.827	0.802	0.828	0.618	0.711	0.839	0.132	0.722	0.633	0.059	0.847	0.092	0.325	0.066		0.353	0.162	0.152
Logistic STAR-GARCH(1,1)	0.641	0.824	0.820	0.796	0.820	0.627	0.718	0.807	0.133	0.724	0.640	0.068	0.862	0.091	0.423	0.090	0.597		0.238	0.239
MS Two-state homoskedastic	0.653	0.981	0.977	0.954	0.978	0.586	0.742	0.838	0.131	0.837	0.623	0.162	0.914	0.298	0.345	0.270	0.406	0.393		0.580
MS Two-state heteroskedastic	0.709	0.938	0.940	0.899	0.951	0.604	0.751	0.779	0.131	0.889	0.883	0.174	0.869	0.314	0.362	0.288	0.414	0.402	0.509	

Note: The table presents p-values for van Dijk and Franses (2003, DF) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in the cells above the main diagonal we report DF p-values for stock return forecasts; below the main diagonal, in each cell we show DF p-values for bond return forecasts.

Table 6 [Cont.]

Van Dijk-Franses Equal Predictive Accuracy Tests (One-Sided)

Panel E: Germany, 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		0.573	0.432	0.542	0.377	0.383	0.768	**0.000**	0.625	0.209	0.275	0.492	0.740	**0.012**	**0.045**	0.165	**0.047**	**0.007**	0.186	0.622
Random walk (with drift)	0.500		0.177	0.295	**0.038**	0.346	0.514	**0.000**	0.618	0.252	0.254	0.130	0.740	**0.006**	**0.034**	0.179	**0.043**	**0.011**	0.144	0.595
AR(1)	0.365	0.358		0.829	0.356	0.493	0.715	**0.000**	0.643	0.354	0.416	0.654	0.778	**0.001**	**0.021**	0.245	**0.046**	**0.012**	0.182	0.731
Random walk (with drift and GARCH(1,1))	0.576	0.987	0.740		**0.003**	0.374	0.559	**0.000**	0.623	0.269	0.289	0.251	0.745	**0.006**	**0.032**	0.193	**0.043**	**0.011**	0.151	0.621
AR(1) with GARCH(1,1)	0.272	0.283	0.113	0.206		0.542	0.799	1.000	0.645	0.354	0.436	1.000	0.779	**0.003**	0.053	0.235	0.061	**0.012**	0.176	0.788
GARCH(1,1) in mean and exogenous predictors	0.221	0.368	0.432	0.309	0.513		0.804	**0.000**	0.641	0.238	0.299	0.585	0.769	**0.001**	**0.044**	0.139	**0.043**	**0.007**	0.145	0.728
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.546	0.515	0.640	0.438	0.721	0.957		**0.000**	0.617	0.162	0.051	0.354	0.741	**0.002**	**0.038**	0.119	**0.033**	**0.009**	0.129	0.591
EGARCH(1,1)-in mean and exogenous predictors	0.264	0.381	0.433	0.326	0.521	0.510	0.225		0.654	**0.000**	**0.000**	1.000	0.870	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	**0.000**	1.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.133	0.346	0.388	0.289	0.474	0.445	0.159	0.420		0.340	0.350	0.370	0.541	0.193	0.207	0.279	0.170	0.091	0.279	0.375
TGARCH(1,1)-in mean and exogenous predictors	0.117	0.278	0.304	0.233	0.371	**0.016**	**0.022**	0.239	0.347		0.765	0.719	0.780	0.079	0.149	0.204	0.123	**0.007**	0.300	0.790
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.188	0.360	0.426	0.299	0.513	0.497	**0.009**	0.490	0.556	0.864		0.700	0.774	**0.020**	0.071	0.139	0.053	**0.011**	0.173	0.805
Exponential STAR - T-bill	0.365	0.358	0.500	0.260	0.887	0.568	0.360	0.567	0.612	0.696	0.574		0.924	0.423	0.751	0.741	**0.000**	**0.029**	0.964	1.000
Exponential STAR-SRF	0.165	0.482	0.609	0.407	0.704	0.750	0.402	0.713	0.844	0.867	0.778	0.672		0.053	0.115	0.160	0.091	**0.046**	0.109	0.260
Logistic STAR - T-bill	0.293	0.414	0.498	0.351	0.575	0.706	0.160	0.585	0.644	0.920	0.683	0.516	0.331		1.000	0.739	**0.000**	0.080	0.950	1.000
Logistic STAR-SRF	0.105	0.500	0.635	0.424	0.727	0.779	0.454	0.735	0.867	0.882	0.812	0.708	0.833	0.707		0.631	**0.000**	**0.013**	0.881	1.000
TAR-SR	0.934	0.789	0.887	0.749	0.919	0.949	0.897	0.945	0.971	0.968	0.939	0.951	0.941	0.935	0.934		0.312	0.056	0.558	0.854
TAR-SRF	0.855	0.856	0.887	0.827	0.912	0.868	0.825	0.864	0.905	0.897	0.872	0.905	0.861	0.858	0.855	0.562		**0.008**	0.879	0.998
Logistic STAR-GARCH(1,1)	0.181	0.358	0.404	0.294	0.517	0.498	0.227	0.491	0.560	0.673	0.499	0.424	0.219	0.416	0.181	**0.017**	0.084		0.995	0.999
MS Two-state homoskedastic	0.729	0.725	0.761	0.685	0.785	0.794	0.728	0.778	0.785	0.837	0.806	0.768	0.739	0.782	0.729	0.462	0.433	0.769		0.985
MS Two-state heteroskedastic	0.510	0.509	0.596	0.442	0.654	0.656	0.495	0.638	0.656	0.754	0.665	0.600	0.529	0.609	0.510	0.213	0.226	0.632	0.126	

Panel F: France, 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		0.719	0.746	0.871	0.906	0.895	0.767	0.789	0.527	0.946	0.887	0.746	0.247	**0.004**	0.916	0.987	0.974	0.957	0.910	0.776
Random walk (with drift)	0.686		0.539	0.948	0.987	0.645	0.477	0.570	0.315	0.728	0.609	0.539	0.209	**0.011**	0.875	0.849	0.809	0.305	0.843	0.641
AR(1)	0.635	0.340		0.862	0.968	0.634	0.459	0.566	0.284	0.721	0.608	0.500	0.207	**0.003**	0.884	0.878	0.871	0.277	0.877	0.660
Random walk (with drift and GARCH(1,1))	0.377	**0.003**	**0.011**		0.621	0.439	0.252	0.373	0.169	0.515	0.343	0.138	0.174	**0.009**	0.848	0.726	0.590	0.138	0.770	0.473
AR(1) with GARCH(1,1)	0.442	0.066	**0.002**	0.762		0.397	0.188	0.334	0.106	0.476	0.291	**0.032**	0.152	**0.003**	0.835	0.718	0.556	0.102	0.765	0.440
GARCH(1,1) in mean and exogenous predictors	0.257	0.272	0.318	0.578	0.509		0.085	0.395	0.129	0.703	0.399	0.366	0.131	**0.007**	0.847	0.858	0.675	0.119	0.811	0.520
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.208	0.191	0.214	0.489	0.408	0.289		0.628	0.235	0.953	0.702	0.541	0.175	**0.009**	0.875	0.934	0.856	0.264	0.866	0.641
EGARCH(1,1)-in mean and exogenous predictors	0.489	0.315	0.363	0.617	0.554	0.610	0.714		0.229	0.711	0.526	0.434	0.185	**0.006**	0.885	0.894	0.755	0.231	0.890	0.581
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.996	0.717	0.782	0.910	0.893	0.993	0.997	0.982		0.924	0.818	0.716	0.206	**0.002**	0.884	0.936	0.914	0.511	0.907	0.748
TGARCH(1,1)-in mean and exogenous predictors	0.871	0.524	0.577	0.758	0.720	0.897	0.866	0.932	0.241		0.232	0.279	0.108	**0.004**	0.829	0.796	0.596	0.062	0.796	0.465
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.981	0.699	0.751	0.881	0.859	0.974	0.971	0.993	0.554	0.899		0.392	0.184	**0.004**	0.887	0.924	0.821	0.125	0.860	0.568
Exponential STAR - T-bill	0.635	0.340	0.500	0.989	0.998	0.682	0.786	0.637	0.218	0.423	0.249		0.479	0.205	0.962	0.999	1.000	0.994	0.976	0.963
Exponential STAR-SRF	0.240	0.256	0.293	0.561	0.489	0.434	0.745	0.367	**0.002**	0.132	**0.022**	0.490		0.387	0.867	0.911	0.872	0.760	0.915	0.822
Logistic STAR - T-bill	0.327	0.314	0.365	0.623	0.558	0.743	0.792	0.511	**0.004**	0.129	**0.019**	0.576	0.760		0.968	0.999	0.999	0.996	0.997	0.999
Logistic STAR-SRF	0.533	0.328	0.396	0.651	0.577	0.604	0.690	0.537	0.134	0.283	0.143	0.573	0.622	0.533		0.210	0.160	0.086	0.327	0.158
TAR-SR	0.856	0.419	0.484	0.737	0.685	0.887	0.887	0.752	0.054	0.321	0.093	0.732	0.889	0.856	0.627		0.228	**0.015**	0.697	0.257
TAR-SRF	0.287	0.262	0.315	0.546	0.480	0.423	0.594	0.348	**0.023**	0.084	**0.027**	0.479	0.475	0.287	0.324	0.125		**0.027**	0.812	0.401
Logistic STAR-GARCH(1,1)	0.776	0.314	0.365	0.623	0.558	0.743	0.792	0.511	**0.004**	0.129	**0.019**	0.576	0.760	0.842	0.467	0.144	0.713		0.907	0.761
MS Two-state homoskedastic	0.824	0.708	0.773	0.875	0.860	0.841	0.910	0.807	0.567	0.658	0.540	0.818	0.874	0.824	0.773	0.760	0.834	0.824		0.143
MS Two-state heteroskedastic	0.867	0.797	0.872	0.945	0.942	0.889	0.950	0.869	0.625	0.706	0.586	0.851	0.916	0.867	0.825	0.808	0.873	0.867	0.581	

Note: The table presents p-values for van Dijk and Franses (2003, DF) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in the cells above the main diagonal we report DF p-values for stock return forecasts; below the main diagonal, in each cell we show DF p-values for bond return forecasts.

Table 6 [Cont.]

Van Dijk-Franses Equal Predictive Accuracy Tests (One-Sided)

Panel G: Canada, 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		0.702	0.680	0.723	0.711	0.795	0.258	0.557	0.207	0.648	0.283	0.680	0.610	0.085	0.085	0.703	0.877	0.860	0.803	0.797
Random walk (with drift)	0.221		0.171	0.878	0.600	0.332	0.191	0.248	0.152	0.308	0.183	0.171	0.298	0.068	0.157	0.368	0.552	0.361	0.625	0.640
AR(1)	0.221	0.623		0.940	0.892	0.363	0.203	0.275	0.160	0.338	0.194	0.500	0.320	0.067	0.163	0.394	0.612	0.393	0.717	0.705
Random walk (with drift and GARCH(1,1))	0.159	0.310	0.288		0.212	0.305	0.170	0.224	0.134	0.284	0.161	0.060	0.276	0.061	0.148	0.347	0.511	0.334	0.574	0.606
AR(1) with GARCH(1,1)	0.170	0.398	0.362	0.840		0.320	0.179	0.240	0.142	0.301	0.170	0.108	0.289	0.066	0.153	0.361	0.538	0.350	0.609	0.640
GARCH(1,1) in mean and exogenous predictors	0.106	0.521	0.508	0.618	0.568		**0.013**	0.321	**0.008**	0.438	**0.021**	0.637	0.206	**0.016**	0.067	0.486	0.870	0.606	0.771	0.780
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.151	0.611	0.602	0.689	0.655	0.795		0.785	0.352	0.793	0.550	0.797	0.763	0.155	0.217	0.770	0.960	0.995	0.900	0.913
EGARCH(1,1)-in mean and exogenous predictors	0.059	0.493	0.483	0.569	0.530	0.433	0.207		0.078	0.649	0.201	0.725	0.455	**0.003**	0.139	0.585	0.917	0.711	0.851	0.824
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.297	0.785	0.781	0.859	0.839	0.972	0.946	0.985		0.880	0.732	0.840	0.821	0.135	0.249	0.797	0.977	0.996	0.933	0.925
TGARCH(1,1)-in mean and exogenous predictors	0.359	0.781	0.778	0.850	0.833	0.959	0.917	0.977	0.682		0.199	0.662	0.353	**0.003**	0.073	0.531	0.924	0.605	0.790	0.759
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.114	0.714	0.712	0.786	0.769	0.879	0.806	0.932	0.401	0.198		0.806	0.738	0.111	0.212	0.742	0.964	0.985	0.915	0.920
Exponential STAR - T-bill	0.221	0.623	0.500	0.712	0.638	0.492	0.398	0.517	0.219	0.222	0.288		0.274	0.188	0.099	0.275	0.496	0.353	0.515	0.529
Exponential STAR-SRF	0.920	0.925	0.928	0.944	0.944	0.942	0.931	0.967	0.910	0.899	0.935	0.813		0.066	0.077	0.690	0.885	0.846	0.804	0.793
Logistic STAR - T-bill	0.608	0.832	0.830	0.901	0.890	0.980	0.910	0.946	0.816	0.771	0.812	0.319	0.154		0.417	0.897	0.999	0.978	0.978	0.950
Logistic STAR-SRF	**0.025**	0.282	0.265	0.339	0.291	0.140	0.070	0.207	**0.005**	**0.018**	**0.025**	**0.013**	**0.022**	**0.026**		0.953	0.983	0.929	0.911	0.882
TAR-SR	0.085	0.514	0.508	0.556	0.536	0.506	0.428	0.528	0.256	0.195	0.234	0.097	**0.031**	0.117	0.695		0.801	0.559	0.712	0.708
TAR-SRF	0.335	0.720	0.716	0.781	0.762	0.796	0.715	0.809	0.467	0.399	0.514	0.260	0.107	0.290	0.934	0.704		0.201	0.544	0.565
Logistic STAR-GARCH(1,1)	0.073	0.200	0.195	0.256	0.230	0.056	0.056	0.186	**0.026**	**0.035**	0.071	**0.042**	**0.049**	**0.027**	0.391	0.320	0.086		0.741	0.755
MS Two-state homoskedastic	0.423	0.754	0.755	0.814	0.807	0.724	0.653	0.744	0.514	0.471	0.538	0.301	0.131	0.377	0.869	0.687	0.526	0.842		0.549
MS Two-state heteroskedastic	0.368	0.703	0.703	0.767	0.755	0.675	0.601	0.694	0.453	0.415	0.479	0.250	0.114	0.326	0.835	0.639	0.475	0.814	0.082	

Panel H: Italy, 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		0.082	0.081	0.073	0.064	0.123	0.518	0.891	0.665	0.129	0.263	0.080	0.102	0.156	0.332	0.358	0.106	0.080	0.748	0.724
Random walk (with drift)	0.941		0.338	0.766	0.450	0.867	0.827	0.936	0.796	0.729	0.660	0.275	0.460	0.401	0.681	0.718	0.392	0.375	0.892	0.911
AR(1)	0.408	**0.007**		0.809	0.609	0.879	0.845	0.957	0.813	0.765	0.692	0.656	0.486	0.415	0.718	0.751	0.412	0.395	0.901	0.921
Random walk (with drift and GARCH(1,1))	0.770	**0.025**	0.903		0.234	0.878	0.835	0.951	0.794	0.711	0.634	0.224	0.412	0.367	0.647	0.688	0.348	0.330	0.905	0.928
AR(1) with GARCH(1,1)	0.421	**0.030**	0.472	0.112		0.903	0.867	0.979	0.827	0.790	0.703	0.546	0.469	0.399	0.724	0.760	0.390	0.372	0.914	0.932
GARCH(1,1) in mean and exogenous predictors	0.700	0.182	0.688	0.385	0.685		0.687	0.982	0.729	0.142	0.318	0.131	0.154	0.191	0.410	0.452	0.145	0.118	0.885	0.846
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.288	**0.017**	0.439	0.104	0.476	0.225		1.000	0.717	**0.050**	0.081	0.171	0.159	0.161	0.343	0.367	0.159	0.127	0.781	0.740
EGARCH(1,1)-in mean and exogenous predictors	0.809	0.411	0.837	0.650	0.862	0.741	0.898		0.358	**0.000**	**0.000**	0.063	0.065	0.082	0.170	0.090	0.069	0.058	0.178	**0.000**
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.646	0.154	0.737	0.374	0.781	0.515	0.792	0.153		0.162	0.116	0.203	0.137	0.125	0.259	0.254	0.146	0.123	0.432	0.447
TGARCH(1,1)-in mean and exogenous predictors	0.825	0.248	0.806	0.514	0.794	0.830	0.890	0.346	0.601		0.483	0.268	0.249	0.239	0.542	0.603	0.215	0.183	0.963	0.931
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.363	**0.006**	0.460	0.056	0.498	0.264	0.560	0.110	0.196	0.137		0.338	0.290	0.236	0.545	0.599	0.256	0.223	0.899	0.855
Exponential STAR - T-bill	0.408	**0.007**	0.500	0.097	0.528	0.312	0.561	0.163	0.263	0.194	0.540		0.712	0.466	0.898	0.948	0.532	0.470	0.941	0.894
Exponential STAR-SRF	0.129	**0.044**	0.382	0.164	0.422	0.180	0.383	0.153	0.267	0.114	0.382	0.430		0.339	0.949	0.985	0.328	0.107	0.881	0.839
Logistic STAR - T-bill	0.397	0.086	0.468	0.228	0.489	0.303	0.505	0.210	0.324	0.203	0.488	0.531	0.586		0.937	0.929	0.557	0.528	0.849	0.813
Logistic STAR-SRF	0.124	**0.028**	0.182	0.074	0.225	0.096	0.210	0.094	0.138	0.066	0.198	0.252	0.322	0.162		1.000	0.052	**0.010**	0.736	0.704
TAR-SR	0.533	0.150	0.603	0.326	0.602	0.398	0.633	0.273	0.414	0.293	0.606	0.736	0.684	0.657	0.828		0.090	**0.022**	0.725	0.694
TAR-SRF	0.807	0.348	0.839	0.585	0.849	0.681	0.854	0.448	0.655	0.572	0.840	0.815	0.844	0.841	0.983	0.753		0.361	0.871	0.840
Logistic STAR-GARCH(1,1)	0.393	0.054	0.583	0.216	0.574	0.288	0.705	0.180	0.340	0.167	0.630	0.597	0.841	0.593	0.876	0.460	0.185		0.898	0.862
MS Two-state homoskedastic	0.505	0.151	0.553	0.286	0.563	0.388	0.581	0.196	0.361	0.292	0.572	0.562	0.627	0.565	0.821	0.487	0.252	0.512		0.519
MS Two-state heteroskedastic	0.956	0.767	0.959	0.905	0.979	0.931	0.975	0.880	0.952	0.899	0.969	0.925	0.954	0.934	0.978	0.919	0.875	0.960	0.952	

Note: The table presents p-values for van Dijk and Franses (2003, DF) tests of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in the cells above the main diagonal we report DF p-values for stock return forecasts; below the main diagonal, in each cell we show DF p-values for bond return forecasts.

Table 7

Sub-Sample Predictive Accuracy Measures for Stock and Bond Returns

Panel A: United States, 1-month Horizon

1995:02-1999:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	4.081	2.178	1.062	0.903	15.529	3.926	0.813	0.563	0.000	0.001	0.110	0.001
Random walk (with drift)	4.033	1.897	1.019	**0.097**	**15.226**	3.590	0.813	0.729	**0.031**	0.069	0.093	**0.160**
AR(1)	4.031	**1.878**	0.984	**0.074**	15.277	**3.522**	0.813	**0.729**	0.013	0.015	0.146	**0.935**
Random walk (with drift and GARCH(1,1))	4.088	1.929	1.143	0.232	15.404	3.668	**0.813**	**0.729**	0.027	**0.143**	0.055	0.011
AR(1) with GARCH(1,1)	4.073	1.910	1.096	**0.204**	15.386	3.605	0.813	**0.729**	0.008	0.003	0.101	**0.575**
GARCH(1,1) in mean and exogenous predictors	4.203	2.170	1.214	0.891	16.189	3.914	0.750	0.563	0.001	0.003	0.028	0.002
GARCH(1,1)-in mean and exogenous predictors - t dist.	4.039	2.158	**0.363**	0.890	16.182	3.866	0.792	0.583	0.000	0.005	**0.178**	0.002
EGARCH(1,1)-in mean and exogenous predictors	4.050	2.113	**0.474**	0.706	16.176	3.967	0.771	0.563	0.003	0.000	0.146	0.006
EGARCH(1,1)-in mean and exogenous predictors- t dist.	4.095	2.176	0.562	0.874	16.451	3.972	0.750	0.583	0.000	0.009	0.095	0.001
TGARCH(1,1)-in mean and exogenous predictors	4.068	2.158	0.732	0.854	16.016	3.929	0.792	0.521	0.002	0.000	0.122	0.002
TGARCH(1,1)-in mean and exogenous predictors- t dist.	**4.025**	2.178	**0.395**	0.918	16.048	3.902	0.813	0.583	0.000	0.010	**0.209**	0.001
Exponential STAR - T-bill	4.471	2.212	1.187	0.842	18.585	4.185	0.625	0.583	0.002	0.041	0.002	0.000
Exponential STAR-SRF	4.081	2.028	1.062	0.583	15.529	3.772	**0.813**	0.688	0.000	0.027	0.110	0.021
Logistic STAR - T-bill	4.065	2.173	0.876	0.934	15.760	3.849	0.813	0.479	0.000	0.000	0.132	0.002
Logistic STAR-SRF	4.081	1.977	1.062	0.518	15.529	3.640	**0.813**	0.667	0.000	0.013	0.110	0.093
TAR-SR	4.366	2.287	1.202	0.990	17.619	4.252	0.604	0.500	0.002	0.000	0.005	0.000
TAR-SRF	4.108	2.179	1.068	0.901	15.733	3.934	0.792	0.500	0.000	0.001	0.082	0.001
Logistic STAR-GARCH(1,1)	4.312	2.100	0.801	0.877	17.947	3.642	0.667	0.542	0.006	0.039	0.008	0.003
MS Two-state homoskedastic	**3.794**	**1.867**	1.152	0.636	**13.066**	**3.082**	0.771	0.708	**0.140**	**0.153**	0.101	0.039
MS Two-state heteroskedastic	**3.745**	**1.845**	0.964	0.566	**13.091**	**3.083**	0.792	0.667	**0.136**	**0.158**	**0.204**	0.059

1999:02-2003:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	5.647	2.159	-1.484	-0.221	29.682	4.610	0.417	0.542	0.018	0.002	0.027	0.092
Random walk (with drift)	5.582	2.075	-1.885	-0.264	27.610	4.237	0.458	0.583	0.011	**0.244**	0.052	0.001
AR(1)	5.606	2.068	-1.846	-0.228	28.022	**4.224**	0.458	**0.583**	0.011	0.004	0.043	**0.623**
Random walk (with drift and GARCH(1,1))	5.563	2.072	-1.839	**-0.120**	27.571	4.280	0.458	**0.583**	0.007	0.101	**0.067**	0.053
AR(1) with GARCH(1,1)	5.581	**2.067**	-1.768	**-0.097**	28.021	4.263	0.458	0.563	0.002	0.001	0.066	**0.676**
GARCH(1,1) in mean and exogenous predictors	5.615	2.146	-0.941	-0.165	30.644	4.579	0.396	0.521	0.013	0.000	0.038	0.123
GARCH(1,1)-in mean and exogenous predictors - t dist.	5.831	2.168	-2.350	-0.186	28.476	4.665	0.458	0.521	0.002	0.000	0.009	0.078
EGARCH(1,1)-in mean and exogenous predictors	5.552	2.145	**-0.891**	-0.479	30.025	4.371	0.417	0.583	0.024	0.002	0.051	0.122
EGARCH(1,1)-in mean and exogenous predictors- t dist.	5.709	2.180	-2.276	-0.358	**27.417**	4.623	0.458	0.563	0.017	0.000	0.016	0.060
TGARCH(1,1)-in mean and exogenous predictors	**5.491**	2.156	**0.052**	-0.205	30.152	4.605	**0.500**	0.563	0.019	0.000	**0.092**	0.101
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.844	2.162	-2.398	-0.226	28.405	4.621	0.458	0.521	0.004	0.000	0.008	0.089
Exponential STAR - T-bill	5.707	2.404	-1.334	-0.195	30.790	5.741	0.479	0.521	**0.038**	0.001	0.010	0.001
Exponential STAR-SRF	5.647	2.366	-1.484	**-0.104**	29.681	5.588	0.417	0.563	0.018	0.001	0.027	0.001
Logistic STAR - T-bill	5.639	2.611	-1.600	-0.542	29.238	6.525	0.479	**0.583**	0.000	0.014	0.043	0.000
Logistic STAR-SRF	5.647	2.137	-1.484	-0.150	29.682	4.546	0.417	0.563	0.018	0.002	0.027	0.143
TAR-SR	5.849	2.233	-1.640	-0.202	31.525	4.945	0.500	0.500	0.008	0.000	0.007	0.020
TAR-SRF	10.904	2.226	**-0.819**	-0.402	118.216	4.792	0.375	0.521	0.035	0.012	0.000	0.017
Logistic STAR-GARCH(1,1)	5.626	2.308	-1.298	0.378	29.972	5.184	0.375	0.479	0.029	0.001	0.024	0.004
MS Two-state homoskedastic	**4.615**	**1.902**	-1.581	0.206	**18.797**	**3.577**	**0.583**	0.563	**0.323**	**0.155**	0.055	**0.658**
MS Two-state heteroskedastic	**4.825**	**1.880**	-1.070	0.123	**22.139**	**3.518**	**0.604**	0.583	**0.202**	**0.178**	**0.311**	0.603

2003:02-2007:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	2.204	2.132	0.721	-0.365	**4.338**	4.414	0.646	0.625	0.186	0.000	0.072	0.086
Random walk (with drift)	2.314	2.098	0.131	-0.547	5.339	4.101	0.708	0.646	0.080	**0.015**	0.125	0.129
AR(1)	2.302	2.112	0.131	-0.470	5.281	4.238	0.708	0.625	0.009	0.003	**0.886**	0.126
Random walk (with drift and GARCH(1,1))	2.340	**2.077**	0.121	-0.471	5.462	**4.093**	**0.708**	0.646	0.049	0.000	0.162	**0.288**
AR(1) with GARCH(1,1)	2.326	2.097	**0.116**	-0.407	5.397	4.230	0.708	0.625	0.002	0.002	0.643	0.177
GARCH(1,1) in mean and exogenous predictors	2.254	2.132	0.535	-0.377	4.792	4.402	0.583	0.667	0.130	0.004	0.119	0.080
GARCH(1,1)-in mean and exogenous predictors - t dist.	2.196	2.152	0.244	-0.439	4.763	4.439	0.625	0.646	0.114	0.004	0.591	0.051
EGARCH(1,1)-in mean and exogenous predictors	**2.119**	2.217	0.350	-0.639	4.367	4.508	0.625	0.667	0.180	0.000	0.522	0.014
EGARCH(1,1)-in mean and exogenous predictors- t dist.	2.233	2.210	0.228	-0.491	4.934	4.643	0.604	0.646	0.090	0.015	0.508	0.012
TGARCH(1,1)-in mean and exogenous predictors	**2.150**	2.180	**-0.025**	-0.528	4.620	4.472	0.708	**0.688**	0.133	0.004	**0.957**	0.029
TGARCH(1,1)-in mean and exogenous predictors- t dist.	2.207	2.178	0.204	-0.533	4.831	4.458	0.625	0.646	0.104	0.002	0.603	0.031
Exponential STAR - T-bill	2.357	2.264	0.710	-0.380	5.051	4.982	0.563	0.521	0.124	0.013	0.018	0.004
Exponential STAR-SRF	2.204	2.204	0.721	-0.521	4.338	4.585	0.646	0.563	**0.186**	0.005	0.072	0.017
Logistic STAR - T-bill	2.437	2.519	0.555	-0.552	5.631	6.043	0.542	0.604	0.033	0.000	0.037	0.000
Logistic STAR-SRF	2.204	2.131	0.721	-0.381	**4.338**	4.397	0.646	0.604	**0.186**	0.002	0.072	0.085
TAR-SR	2.296	2.142	0.748	-0.374	4.713	4.447	0.500	0.604	0.134	0.000	0.044	0.070
TAR-SRF	3.094	2.301	0.891	**-0.133**	8.777	5.277	0.604	0.625	0.024	0.001	0.000	0.003
Logistic STAR-GARCH(1,1)	2.310	2.262	**0.104**	**-0.329**	5.323	5.010	**0.708**	0.521	0.082	0.001	0.130	0.006
MS Two-state homoskedastic	**2.028**	**1.947**	0.200	-0.329	**4.072**	**3.683**	**0.771**	**0.688**	**0.242**	**0.103**	0.640	**0.470**
MS Two-state heteroskedastic	2.157	**1.914**	0.245	**-0.268**	4.595	**3.592**	0.708	**0.750**	0.136	**0.132**	**0.741**	**0.481**

Panel B: United Kingdom, 1-month Horizon

1995:02-1999:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	3.915	1.022	1.533	0.473	12.974	0.822	0.521	0.771	0.067	0.003	0.021	0.000
Random walk (with drift)	3.737	**0.814**	**0.087**	**-0.007**	13.954	**0.662**	**0.729**	**0.854**	0.097	**0.062**	0.085	**0.204**
AR(1)	3.742	0.867	**0.090**	**0.003**	13.992	0.752	0.729	**0.854**	0.013	0.006	0.621	**0.042**
Random walk (with drift and GARCH(1,1))	3.720	0.840	0.136	0.157	13.818	0.681	0.729	0.854	0.009	0.018	**0.896**	**0.133**
AR(1) with GARCH(1,1)	3.757	0.891	0.174	**0.147**	14.081	0.772	0.729	0.854	0.029	0.005	0.354	0.012
GARCH(1,1) in mean and exogenous predictors	4.475	0.970	2.256	0.387	14.935	0.791	0.458	0.771	0.022	0.000	0.000	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	**3.608**	0.982	0.369	0.422	12.879	0.785	0.729	0.792	0.078	0.000	0.689	0.000
EGARCH(1,1)-in mean and exogenous predictors	3.772	0.958	-0.302	0.353	14.137	0.792	0.708	0.792	0.008	0.000	0.483	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	**3.708**	0.964	**0.027**	0.354	13.750	0.803	0.688	0.792	0.016	0.001	**0.871**	0.000
TGARCH(1,1)-in mean and exogenous predictors	3.778	0.974	0.188	0.397	14.235	0.791	0.625	0.771	0.004	0.000	0.489	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	3.728	0.981	0.229	0.424	13.849	0.782	0.646	0.813	0.013	0.000	**0.728**	0.000
Exponential STAR - T-bill	3.909	0.988	1.553	0.458	**12.872**	0.766	0.563	0.771	0.076	0.000	0.018	0.000
Exponential STAR-SRF	3.967	1.030	1.262	0.481	14.140	0.829	0.625	0.750	0.047	0.000	0.019	0.000
Logistic STAR - T-bill	3.955	1.001	0.253	0.267	15.579	0.931	0.646	0.792	0.001	0.020	0.063	0.000
Logistic STAR-SRF	3.885	1.030	1.657	0.481	**12.349**	0.829	0.563	0.750	**0.117**	0.000	0.009	0.000
TAR-SR	3.939	0.977	1.519	0.453	13.209	0.749	0.500	0.729	0.058	0.025	0.020	0.000
TAR-SRF	4.111	1.080	1.294	0.311	15.226	1.070	0.542	0.750	0.021	0.007	0.007	0.000
Logistic STAR-GARCH(1,1)	4.035	0.991	1.423	0.425	14.255	0.803	0.583	0.750	0.001	0.000	0.025	0.000
MS Two-state homoskedastic	**3.098**	**0.763**	0.848	0.256	**8.876**	**0.516**	**0.771**	**0.854**	**0.531**	**0.260**	0.000	0.017
MS Two-state heteroskedastic	3.753	**0.792**	0.867	0.353	13.331	**0.503**	**0.771**	0.833	**0.103**	**0.270**	0.061	0.002

1999:02-2003:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	4.956	**1.317**	-0.241	0.157	24.500	1.710	0.500	0.604	0.000	0.010	0.499	**0.112**
Random walk (with drift)	5.207	1.337	-1.853	-0.415	23.684	**1.614**	0.521	**0.646**	0.024	**0.150**	0.030	0.002
AR(1)	5.222	1.339	-1.818	-0.293	23.963	1.707	0.521	0.646	0.002	0.000	0.043	0.065
Random walk (with drift and GARCH(1,1))	5.203	1.327	-1.815	-0.379	23.781	1.619	0.521	0.646	0.003	0.024	0.049	0.056
AR(1) with GARCH(1,1)	5.213	1.334	-1.852	-0.267	23.745	1.707	0.521	0.646	0.004	0.000	0.044	0.079
GARCH(1,1) in mean and exogenous predictors	5.190	1.338	**-0.083**	0.080	26.927	1.783	0.458	0.625	0.004	0.003	0.054	0.064
GARCH(1,1)-in mean and exogenous predictors - t dist.	5.085	1.324	-1.121	0.126	24.604	1.738	0.500	0.625	0.000	0.005	0.151	0.097
EGARCH(1,1)-in mean and exogenous predictors	5.222	1.336	-0.166	0.150	27.242	1.763	0.354	0.583	0.086	0.007	0.006	0.062
EGARCH(1,1)-in mean and exogenous predictors- t dist.	5.114	1.333	-0.908	0.136	25.329	1.758	0.438	0.604	0.011	0.002	0.091	0.076
TGARCH(1,1)-in mean and exogenous predictors	5.375	1.339	-0.442	0.084	28.697	1.785	0.313	0.646	0.052	0.005	0.004	0.059
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.049	1.331	-0.347	0.153	25.375	1.748	0.375	0.583	0.008	0.006	0.176	0.076
Exponential STAR - T-bill	4.795	1.474	**-0.213**	0.265	22.945	2.104	0.563	0.563	0.042	0.000	**0.845**	0.001
Exponential STAR-SRF	4.942	1.335	-0.320	0.182	24.322	1.749	0.542	0.563	0.006	0.010	0.490	0.059
Logistic STAR - T-bill	**4.521**	1.366	**0.056**	0.186	**20.435**	1.832	**0.667**	0.604	**0.143**	0.001	**0.989**	0.026
Logistic STAR-SRF	4.959	1.335	-0.231	0.182	24.539	1.749	0.521	0.563	0.000	0.010	0.481	0.059
TAR-SR	5.204	1.388	-0.399	**0.054**	26.918	1.923	0.458	0.500	0.040	0.005	0.021	0.011
TAR-SRF	5.033	1.333	-0.834	0.108	24.633	1.766	0.583	0.542	0.015	0.009	0.175	0.065
Logistic STAR-GARCH(1,1)	5.015	1.346	-0.346	0.172	25.028	1.782	0.500	0.563	0.000	0.006	0.289	0.045
MS Two-state homoskedastic	**4.438**	**1.060**	-0.384	**-0.033**	**19.549**	**1.122**	**0.750**	**0.750**	**0.192**	**0.332**	**0.596**	**0.287**
MS Two-state heteroskedastic	**4.331**	**1.063**	-0.373	**-0.029**	**18.619**	**1.129**	**0.750**	**0.750**	**0.282**	**0.315**	0.122	**0.440**

2003:02-2007:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	2.854	1.421	1.245	-0.264	6.595	1.948	0.521	0.646	0.087	0.015	0.008	0.020
Random walk (with drift)	2.700	1.446	0.221	-0.597	7.240	**1.733**	0.708	0.646	0.056	0.006	0.212	0.011
AR(1)	2.702	1.425	0.219	-0.460	7.255	1.818	0.708	0.625	0.004	0.001	**0.688**	0.024
Random walk (with drift and GARCH(1,1))	2.714	1.444	0.301	-0.592	7.277	1.736	0.708	0.646	**0.142**	0.009	0.018	0.011
AR(1) with GARCH(1,1)	2.702	1.424	0.326	-0.484	7.195	1.793	0.708	0.646	0.004	0.000	**0.704**	0.025
GARCH(1,1) in mean and exogenous predictors	2.786	1.419	1.062	-0.356	6.634	1.888	0.625	0.604	0.081	0.005	0.027	0.026
GARCH(1,1)-in mean and exogenous predictors - t dist.	**2.550**	1.413	**0.128**	-0.313	6.486	1.899	**0.729**	0.604	0.101	0.008	**0.943**	0.030
EGARCH(1,1)-in mean and exogenous predictors	2.890	1.420	1.266	-0.341	6.748	1.900	0.542	0.646	0.067	0.003	0.007	0.027
EGARCH(1,1)-in mean and exogenous predictors- t dist.	2.667	1.417	**-0.142**	-0.209	7.091	1.964	0.708	0.604	0.034	0.014	0.634	0.023
TGARCH(1,1)-in mean and exogenous predictors	2.704	1.414	0.207	-0.347	7.268	1.880	0.688	0.625	0.024	0.003	0.427	**0.032**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	2.678	1.400	**0.170**	-0.299	7.145	1.871	0.729	0.625	0.035	0.004	0.507	**0.050**
Exponential STAR - T-bill	2.830	1.636	1.195	**-0.017**	6.580	2.675	0.583	**0.667**	0.090	**0.028**	0.011	0.000
Exponential STAR-SRF	2.896	1.423	1.363	-0.237	6.528	1.969	0.542	0.583	0.097	0.009	0.003	0.021
Logistic STAR - T-bill	2.738	1.419	0.640	**-0.200**	7.084	1.972	0.583	0.542	0.065	0.001	0.090	0.030
Logistic STAR-SRF	2.898	1.423	1.238	-0.237	6.868	1.969	0.542	0.583	0.065	0.009	0.007	0.021
TAR-SR	2.774	1.446	1.128	**-0.195**	**6.424**	2.054	0.646	0.583	0.110	0.020	0.016	0.008
TAR-SRF	3.045	**1.392**	1.381	-0.302	7.368	1.846	0.458	0.646	0.034	0.002	0.001	**0.069**
Logistic STAR-GARCH(1,1)	2.922	1.413	1.178	-0.257	7.148	1.932	0.542	0.604	0.041	0.004	0.008	0.033
MS Two-state homoskedastic	**2.213**	**1.175**	0.807	-0.262	**4.248**	**1.311**	**0.750**	**0.708**	**0.549**	**0.378**	0.000	0.003
MS Two-state heteroskedastic	**2.194**	**1.165**	0.817	-0.265	**4.147**	**1.287**	**0.792**	**0.688**	**0.603**	**0.390**	0.000	0.003

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

Table 7 [Cont.]

Sub-Sample Predictive Accuracy Measures for Stock and Bond Returns

Panel C: Japan, 1-month Horizon

1995:02-1999:01

Measure	RMSFE		Bias		Forecast Variance		Success Ratio		MZ regression (R-square)		MZ (p-value for intercept =0 and coefficient =1)	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	5.500	2.475	-0.921	0.217	29.401	6.079	0.458	0.583	0.002	0.001	0.093	0.032
Random walk (with drift)	**5.369**	**2.304**	-1.186	**-0.007**	**27.421**	**5.309**	0.438	**0.646**	0.011	**0.150**	**0.230**	0.021
AR(1)	**5.346**	**2.311**	-1.118	**-0.005**	**27.333**	5.340	0.417	0.646	0.001	**0.068**	**0.348**	0.153
Random walk (with drift and GARCH(1,1))	5.471	**2.310**	-1.572	-0.094	27.458	**5.329**	0.438	0.646	0.009	0.025	0.102	**0.441**
AR(1) with GARCH(1,1)	**5.427**	2.312	-1.460	**-0.093**	**27.318**	**5.339**	0.438	0.646	0.003	0.017	0.167	**0.514**
GARCH(1,1) in mean and exogenous predictors	5.669	2.514	-1.150	0.255	30.812	6.254	0.354	**0.667**	0.034	0.017	0.011	0.011
GARCH(1,1)-in mean and exogenous predictors - t dist.	5.828	2.487	-0.680	0.177	33.504	6.154	0.375	0.604	**0.090**	0.022	0.001	0.016
EGARCH(1,1)-in mean and exogenous predictors	5.507	2.479	**-0.384**	0.233	30.176	6.093	**0.479**	0.625	0.008	0.010	0.076	0.025
EGARCH(1,1)-in mean and exogenous predictors- t dist.	5.788	2.478	**0.099**	0.197	33.490	6.101	0.458	0.563	**0.064**	0.015	0.002	0.023
TGARCH(1,1)-in mean and exogenous predictors	5.491	2.517	-0.543	0.256	29.854	6.269	0.479	**0.667**	0.003	0.018	0.099	0.010
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.543	2.488	-0.636	0.181	30.325	6.159	0.479	0.604	0.015	0.024	0.047	0.015
Exponential STAR - T-bill	5.677	2.801	-0.948	0.211	31.326	7.802	**0.521**	0.625	0.002	0.015	0.022	0.000
Exponential STAR-SRF	5.883	2.341	-0.678	0.159	34.152	5.454	0.375	0.604	**0.037**	0.020	0.002	**0.275**
Logistic STAR - T-bill	5.594	2.465	-0.881	0.323	30.518	5.970	0.438	0.604	0.005	0.004	0.040	0.037
Logistic STAR-SRF	5.845	2.729	-0.839	0.247	33.461	7.388	0.375	0.583	0.010	0.007	0.005	0.000
TAR-SR	5.449	2.622	-0.684	0.290	29.220	6.789	**0.521**	0.563	0.001	0.002	**0.146**	0.002
TAR-SRF	5.820	2.528	-0.840	0.242	33.167	6.332	0.458	0.563	0.008	0.005	0.006	0.011
Logistic STAR-GARCH(1,1)	5.792	2.414	-1.309	0.140	31.829	5.806	0.396	0.625	0.007	0.004	0.008	0.096
MS Two-state homoskedastic	5.563	2.680	**-0.379**	0.306	30.802	7.089	0.396	0.479	0.001	**0.043**	0.057	0.000
MS Two-state heteroskedastic	5.496	2.570	-0.482	0.243	29.972	6.547	0.417	0.500	0.001	0.018	0.098	0.004

1999:02-2003:01

Measure	RMSFE		Bias		Forecast Variance		Success Ratio		MZ regression (R-square)		MZ (p-value for intercept =0 and coefficient =1)	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	5.856	1.155	-0.428	-0.127	34.108	1.318	0.500	**0.667**	0.016	0.110	0.180	0.545
Random walk (with drift)	**5.758**	1.234	-0.948	-0.232	32.254	1.468	0.479	0.604	0.006	0.027	**0.490**	0.207
AR(1)	**5.743**	1.233	-0.884	-0.235	**32.202**	1.465	0.500	0.604	0.004	0.005	**0.575**	0.358
Random walk (with drift and GARCH(1,1))	5.810	1.239	-1.233	-0.235	**32.233**	1.480	0.479	0.604	0.006	0.001	0.325	0.308
AR(1) with GARCH(1,1)	5.792	1.243	-1.134	-0.225	32.261	1.494	0.479	0.604	0.005	0.006	0.385	0.239
GARCH(1,1) in mean and exogenous predictors	5.906	**1.119**	-0.568	**-0.032**	34.560	**1.251**	0.479	0.646	0.021	**0.147**	0.106	**0.896**
GARCH(1,1)-in mean and exogenous predictors - t dist.	6.021	1.162	-0.569	-0.136	35.934	1.331	0.396	**0.667**	**0.114**	0.095	0.004	0.624
EGARCH(1,1)-in mean and exogenous predictors	5.804	1.143	**-0.242**	**-0.079**	33.625	1.300	0.542	0.646	0.001	0.122	0.379	**0.651**
EGARCH(1,1)-in mean and exogenous predictors- t dist.	6.117	1.157	**0.179**	-0.151	37.388	1.316	0.479	0.625	**0.055**	0.106	0.009	0.556
TGARCH(1,1)-in mean and exogenous predictors	5.870	**1.122**	-0.334	**-0.047**	34.339	1.256	0.542	0.646	0.003	0.145	0.218	**0.851**
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.888	1.166	-0.376	-0.148	34.530	1.337	0.500	0.646	0.010	0.092	0.160	0.568
Exponential STAR - T-bill	5.942	1.131	-0.242	-0.203	35.249	**1.238**	0.542	0.667	0.019	**0.163**	0.085	0.358
Exponential STAR-SRF	5.982	1.311	-0.434	-0.193	35.601	1.682	0.458	0.583	0.006	0.023	0.085	0.014
Logistic STAR - T-bill	5.338	1.171	-0.833	-0.090	**27.798**	1.363	0.479	0.646	**0.142**	0.093	**0.543**	0.454
Logistic STAR-SRF	6.065	**1.121**	**-0.283**	-0.089	36.709	**1.249**	0.479	0.646	0.009	**0.172**	0.042	0.408
TAR-SR	6.207	1.243	-0.668	-0.188	38.084	1.509	0.521	**0.667**	0.033	0.055	0.008	0.076
TAR-SRF	6.046	1.285	-0.305	-0.103	36.461	1.640	0.417	0.604	0.040	0.030	0.023	0.030
Logistic STAR-GARCH(1,1)	5.955	1.152	-0.475	-0.172	35.236	1.297	**0.604**	0.646	0.002	0.112	0.115	0.595
MS Two-state homoskedastic	5.825	1.536	-0.338	-0.090	33.822	2.351	**0.583**	0.458	0.005	0.006	0.294	0.000
MS Two-state heteroskedastic	**5.788**	1.371	-0.524	-0.103	33.231	1.868	**0.542**	0.542	0.009	0.025	0.358	0.002

2003:02-2007:01

Measure	RMSFE		Bias		Forecast Variance		Success Ratio		MZ regression (R-square)		MZ (p-value for intercept =0 and coefficient =1)	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	3.780	1.440	0.538	-0.614	**14.000**	1.696	**0.729**	0.458	**0.080**	0.007	0.551	0.000
Random walk (with drift)	4.044	**1.309**	1.076	-0.550	15.195	**1.410**	0.646	0.458	0.016	**0.043**	0.115	0.003
AR(1)	3.971	1.311	1.001	-0.557	14.768	**1.410**	0.625	0.458	0.032	**0.027**	0.183	**0.005**
Random walk (with drift and GARCH(1,1))	3.959	**1.283**	0.708	-0.477	15.173	**1.419**	0.646	0.458	0.002	0.002	0.428	**0.022**
AR(1) with GARCH(1,1)	3.867	**1.283**	0.618	**-0.471**	14.575	1.424	0.646	0.458	0.041	0.004	0.501	**0.021**
GARCH(1,1) in mean and exogenous predictors	**3.764**	1.427	**0.043**	-0.577	14.167	1.704	0.667	0.458	0.064	0.012	**0.982**	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	3.814	1.442	**0.130**	-0.615	14.526	1.700	0.646	0.479	0.041	0.013	**0.952**	0.000
EGARCH(1,1)-in mean and exogenous predictors	3.773	1.444	0.356	-0.552	14.109	1.781	0.646	0.417	0.069	0.009	0.798	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	3.908	1.438	0.328	-0.573	15.166	1.738	0.646	0.438	0.009	0.012	0.663	0.000
TGARCH(1,1)-in mean and exogenous predictors	**3.761**	1.433	**0.187**	-0.586	14.108	1.709	0.625	0.458	0.070	0.012	0.903	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	3.801	1.448	0.195	-0.618	14.407	1.714	0.646	0.458	0.048	**0.015**	**0.940**	0.000
Exponential STAR - T-bill	3.953	1.497	0.822	-0.542	14.948	1.947	0.625	**0.521**	0.027	0.000	0.259	0.000
Exponential STAR-SRF	3.846	1.486	0.457	-0.538	14.585	1.919	0.667	0.479	0.037	0.001	0.703	0.000
Logistic STAR - T-bill	3.870	1.477	0.592	-0.707	14.628	1.683	0.708	0.458	0.034	0.006	0.567	0.000
Logistic STAR-SRF	3.806	1.522	0.456	-0.505	14.277	2.062	**0.708**	0.438	0.057	0.004	0.710	0.000
TAR-SR	3.882	1.442	0.455	**-0.440**	14.866	1.887	0.646	**0.521**	0.029	0.002	0.556	0.000
TAR-SRF	**3.591**	1.379	0.825	-0.533	**12.213**	1.617	**0.833**	0.458	**0.212**	0.002	0.168	0.001
Logistic STAR-GARCH(1,1)	3.863	1.414	-0.325	-0.598	14.817	1.641	0.625	0.438	0.033	0.011	0.631	0.000
MS Two-state homoskedastic	3.793	1.323	0.568	**-0.428**	14.064	1.567	0.646	**0.646**	0.073	0.015	0.562	0.004
MS Two-state heteroskedastic	3.777	1.367	0.573	-0.607	**13.939**	1.500	0.667	0.438	**0.080**	0.002	0.567	0.001

Panel D: Germany, 1-month Horizon

1995:02-1999:01

Measure	RMSFE		Bias		Forecast Variance		Success Ratio		MZ regression (R-square)		MZ (p-value for intercept =0 and coefficient =1)	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	5.038	1.614	0.653	0.410	24.956	2.438	0.729	0.750	0.056	0.059	0.677	0.001
Random walk (with drift)	5.210	**1.495**	0.779	0.386	26.534	**2.088**	0.729	**0.792**	0.012	**0.081**	0.408	0.025
AR(1)	5.248	**1.521**	0.702	**0.310**	27.048	**2.219**	0.688	0.771	0.002	0.008	0.374	**0.065**
Random walk (with drift and GARCH(1,1))	5.220	**1.493**	0.916	0.367	26.405	**2.095**	0.667	**0.792**	0.001	**0.074**	0.482	**0.032**
AR(1) with GARCH(1,1)	5.268	1.530	0.852	0.319	27.023	2.238	0.667	0.771	0.000	0.011	0.325	**0.047**
GARCH(1,1) in mean and exogenous predictors	4.998	1.690	0.441	0.663	24.781	2.415	0.729	0.688	0.062	0.028	**0.835**	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	**4.899**	1.664	**0.002**	0.559	24.002	2.456	0.688	0.708	0.092	0.046	**0.992**	0.000
EGARCH(1,1)-in mean and exogenous predictors	5.157	1.690	-1.223	0.640	25.100	2.446	0.729	0.688	0.051	0.029	0.263	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	5.033	1.667	-1.322	0.546	**23.588**	2.483	**0.750**	0.708	**0.133**	0.045	0.099	0.000
TGARCH(1,1)-in mean and exogenous predictors	**4.911**	1.680	-1.208	0.658	**22.659**	2.390	0.750	0.688	**0.181**	0.024	0.082	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.017	1.648	-1.154	0.557	23.834	2.405	**0.750**	0.708	0.104	0.027	0.247	0.001
Exponential STAR - T-bill	5.038	1.612	0.653	0.450	24.956	2.397	0.729	0.771	0.056	0.029	**0.677**	0.003
Exponential STAR-SRF	5.049	1.615	0.759	0.421	24.919	2.431	0.729	0.771	0.057	0.052	0.591	0.001
Logistic STAR - T-bill	**4.946**	1.653	0.864	0.591	**23.720**	2.381	0.688	0.750	**0.120**	0.051	0.315	0.001
Logistic STAR-SRF	5.282	1.614	0.672	0.410	27.444	2.438	**0.750**	0.750	0.010	0.059	0.231	0.001
TAR-SR	5.033	1.718	0.580	0.382	24.990	2.804	0.646	0.729	0.059	**0.071**	0.652	0.000
TAR-SRF	5.189	1.695	0.444	0.384	26.729	2.725	0.646	0.688	0.023	0.010	0.382	0.000
Logistic STAR-GARCH(1,1)	5.291	1.572	**0.055**	**0.206**	27.990	2.430	0.708	**0.771**	0.041	0.047	0.101	0.006
MS Two-state homoskedastic	5.704	1.592	0.446	0.350	32.338	2.411	0.667	0.729	0.042	0.000	0.003	0.010
MS Two-state heteroskedastic	5.479	1.598	**0.374**	**0.341**	29.882	2.437	0.646	0.750	0.005	0.001	0.048	0.008

1999:02-2003:01

Measure	RMSFE		Bias		Forecast Variance		Success Ratio		MZ regression (R-square)		MZ (p-value for intercept =0 and coefficient =1)	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	7.320	1.467	-1.526	-0.133	51.255	2.135	0.417	0.646	0.005	0.013	0.297	0.318
Random walk (with drift)	7.362	1.481	-1.825	-0.302	**50.864**	2.103	0.500	0.604	0.020	**0.200**	0.159	0.002
AR(1)	7.400	**1.424**	-1.654	-0.246	52.023	**1.966**	0.479	0.625	0.001	**0.055**	0.198	**0.470**
Random walk (with drift and GARCH(1,1))	7.301	1.495	-1.244	-0.326	51.763	2.129	0.438	0.604	0.013	**0.237**	0.278	0.000
AR(1) with GARCH(1,1)	7.344	**1.430**	**-1.202**	-0.188	52.483	**2.011**	0.479	0.625	0.004	0.032	0.263	**0.669**
GARCH(1,1) in mean and exogenous predictors	**7.276**	1.450	-1.204	**-0.037**	51.483	2.102	0.458	0.646	0.004	0.027	**0.402**	0.396
GARCH(1,1)-in mean and exogenous predictors - t dist.	7.396	1.460	-1.651	-0.128	51.979	2.116	0.417	**0.646**	0.002	0.020	0.198	0.340
EGARCH(1,1)-in mean and exogenous predictors	7.343	1.459	-1.652	**0.049**	51.190	2.125	0.438	0.625	0.003	0.022	0.266	0.344
EGARCH(1,1)-in mean and exogenous predictors- t dist.	7.395	1.481	-1.673	-0.077	51.895	2.188	**0.542**	0.583	0.000	0.010	0.205	0.221
TGARCH(1,1)-in mean and exogenous predictors	7.521	1.443	**-1.151**	**0.010**	55.234	2.083	0.458	0.604	0.003	0.031	0.089	0.448
TGARCH(1,1)-in mean and exogenous predictors- t dist.	7.507	1.446	-1.785	-0.089	53.173	2.084	0.458	0.646	0.000	0.028	0.104	0.441
Exponential STAR - T-bill	7.320	**1.439**	-1.526	-0.101	51.255	2.061	0.417	**0.688**	0.005	0.044	0.297	0.373
Exponential STAR-SRF	7.303	1.472	-1.527	-0.126	50.998	2.151	0.396	0.646	0.007	0.012	**0.315**	0.279
Logistic STAR - T-bill	7.376	1.458	-1.338	-0.079	52.617	2.118	0.417	0.625	0.000	0.018	0.231	0.384
Logistic STAR-SRF	7.369	1.467	-1.501	-0.133	52.047	2.135	0.458	**0.646**	0.002	0.013	0.234	0.318
TAR-SR	7.496	1.531	**-1.059**	-0.126	55.071	2.329	0.458	0.563	0.003	0.006	0.103	0.053
TAR-SRF	**7.241**	1.597	-1.428	-0.268	**50.395**	2.478	**0.500**	0.625	**0.021**	0.000	**0.339**	0.009
Logistic STAR-GARCH(1,1)	**7.265**	1.441	-2.355	-0.160	**47.235**	2.050	**0.521**	**0.646**	**0.086**	0.028	0.059	**0.521**
MS Two-state homoskedastic	8.172	1.527	-1.984	-0.124	62.854	2.317	0.417	0.625	**0.030**	0.005	0.001	0.061
MS Two-state heteroskedastic	7.749	1.441	-2.214	-0.166	55.140	**2.050**	0.479	0.604	0.010	0.036	0.019	0.419

2003:02-2007:01

Measure	RMSFE		Bias		Forecast Variance		Success Ratio		MZ regression (R-square)		MZ (p-value for intercept =0 and coefficient =1)	
Model	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds	Stocks	Bonds
Linear	**4.067**	**1.274**	0.976	-0.245	**15.590**	**1.562**	**0.729**	0.646	**0.064**	0.047	0.251	0.393
Random walk (with drift)	4.205	1.321	0.998	-0.328	16.689	1.637	0.688	0.625	0.014	0.002	0.179	0.218
AR(1)	4.197	1.310	0.939	-0.279	16.737	1.639	0.729	0.625	0.001	0.008	0.265	0.271
Random walk (with drift and GARCH(1,1))	4.313	1.320	1.215	-0.334	17.125	1.631	0.625	0.625	0.002	0.003	0.074	0.216
AR(1) with GARCH(1,1)	4.280	1.299	1.124	-0.213	17.050	1.641	0.708	**0.646**	0.000	0.008	0.110	0.405
GARCH(1,1) in mean and exogenous predictors	4.225	1.283	1.026	-0.239	16.798	1.589	**0.729**	0.604	0.014	0.036	0.143	0.370
GARCH(1,1)-in mean and exogenous predictors - t dist.	4.122	1.287	**0.708**	-0.286	16.487	1.573	0.646	0.583	0.027	0.042	**0.333**	0.277
EGARCH(1,1)-in mean and exogenous predictors	4.174	1.314	0.890	**-0.088**	16.634	1.719	0.688	0.646	0.014	0.008	0.249	0.237
EGARCH(1,1)-in mean and exogenous predictors- t dist.	4.158	1.244	0.747	**-0.018**	16.726	1.547	0.646	0.646	0.017	**0.057**	**0.283**	**0.916**
TGARCH(1,1)-in mean and exogenous predictors	4.209	1.281	1.029	-0.225	16.658	1.589	0.688	0.625	0.016	0.036	0.162	0.401
TGARCH(1,1)-in mean and exogenous predictors- t dist.	4.142	1.285	0.761	-0.280	16.576	1.572	0.667	0.583	0.022	0.044	**0.299**	0.290
Exponential STAR - T-bill	**4.067**	1.275	0.976	-0.241	**15.590**	1.566	**0.729**	0.646	**0.064**	0.046	0.251	0.397
Exponential STAR-SRF	5.347	1.274	**0.573**	-0.232	28.265	1.569	0.708	0.625	0.029	0.044	0.000	**0.424**
Logistic STAR - T-bill	**4.050**	1.280	0.997	-0.288	**15.408**	**1.554**	0.625	**0.646**	**0.075**	0.052	0.234	0.280
Logistic STAR-SRF	4.747	**1.274**	1.198	-0.245	21.100	1.562	0.604	0.646	0.028	0.047	0.000	0.393
TAR-SR	4.253	1.305	0.985	**-0.097**	17.118	1.693	0.667	0.625	0.020	0.028	0.093	0.206
TAR-SRF	4.472	1.334	1.507	-0.114	17.727	1.767	0.604	0.625	0.019	0.013	0.009	0.105
Logistic STAR-GARCH(1,1)	4.735	**1.243**	1.179	-0.156	21.027	**1.520**	0.646	**0.667**	0.001	**0.072**	0.001	**0.666**
MS Two-state homoskedastic	4.526	1.518	0.738	-0.292	19.980	2.219	0.688	0.583	0.041	**0.086**	0.003	0.000
MS Two-state heteroskedastic	4.215	1.426	**0.432**	-0.274	17.580	1.957	0.708	0.563	0.034	0.037	0.100	0.003

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

Table 7 [Cont.]

Sub-Sample Predictive Accuracy Measures for Stock and Bond Returns

Panel E: France, 1-month Horizon

1995:02-1999:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	5.677	1.568	1.086	0.142	**31.049**	2.439	0.688	0.813	0.025	0.002	0.341	0.005
Random walk (with drift)	5.650	**1.420**	0.501	0.206	31.675	**1.973**	0.688	**0.813**	0.026	**0.111**	0.418	**0.036**
AR(1)	5.673	**1.482**	**0.491**	0.174	31.945	**2.165**	0.667	**0.813**	0.001	0.024	**0.620**	**0.043**
Random walk (with drift and GARCH(1,1))	5.710	**1.442**	0.693	0.239	32.122	**2.022**	0.688	**0.813**	0.006	0.034	0.415	**0.118**
AR(1) with GARCH(1,1)	5.745	1.487	0.660	0.217	32.565	2.165	0.667	0.813	0.008	**0.054**	0.300	0.018
GARCH(1,1) in mean and exogenous predictors	5.987	1.585	1.844	0.201	32.450	2.472	0.646	0.813	0.017	0.001	0.036	0.003
GARCH(1,1)-in mean and exogenous predictors - t dist.	5.849	1.558	1.653	0.311	31.474	2.331	0.646	0.813	0.028	0.001	0.082	0.007
EGARCH(1,1)-in mean and exogenous predictors	6.101	1.582	2.130	-0.185	32.684	2.469	0.646	0.813	0.013	0.006	0.017	0.003
EGARCH(1,1)-in mean and exogenous predictors- t dist.	5.847	1.559	1.526	**0.039**	31.858	2.429	0.583	0.813	0.018	0.006	0.103	0.006
TGARCH(1,1)-in mean and exogenous predictors	5.976	1.637	2.002	**-0.026**	31.705	2.680	0.625	0.813	0.023	0.010	0.034	0.001
TGARCH(1,1)-in mean and exogenous predictors- t dist.	5.952	1.595	1.668	-0.068	32.647	2.538	0.646	0.813	0.011	0.019	0.055	0.002
Exponential STAR - T-bill	**5.295**	1.538	**0.436**	**0.058**	27.843	2.362	**0.708**	0.792	**0.145**	0.035	**0.420**	0.006
Exponential STAR-SRF	**5.198**	1.563	1.744	0.146	**23.975**	2.421	0.667	0.792	**0.263**	0.001	0.031	0.006
Logistic STAR - T-bill	**5.468**	1.568	1.143	0.142	**28.588**	2.439	**0.729**	0.813	**0.095**	0.002	0.354	0.005
Logistic STAR-SRF	6.970	1.536	0.506	0.161	48.329	2.333	0.625	0.771	0.008	0.001	0.000	0.014
TAR-SR	6.002	1.652	1.266	0.130	34.424	2.713	0.667	0.792	0.018	0.009	0.032	0.000
TAR-SRF	5.681	1.636	**0.489**	0.155	32.038	2.651	0.646	0.771	0.014	0.001	**0.433**	0.001
Logistic STAR-GARCH(1,1)	5.685	1.568	1.057	0.142	31.207	2.439	**0.688**	0.813	0.022	0.002	0.346	0.005
MS Two-state homoskedastic	6.218	1.600	1.579	0.206	36.173	2.519	0.458	0.813	0.005	0.016	0.008	0.002
MS Two-state heteroskedastic	6.277	1.642	1.593	0.113	36.862	2.683	0.521	0.813	0.011	**0.056**	0.005	0.000

1999:02-2003:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	6.956	1.747	-0.689	0.055	47.911	3.048	0.333	0.521	0.067	0.000	0.016	0.001
Random walk (with drift)	**6.746**	1.624	-1.550	-0.581	43.110	**2.298**	**0.521**	**0.604**	0.018	**0.243**	**0.206**	0.000
AR(1)	**6.758**	**1.581**	-1.464	-0.469	43.532	**2.280**	0.479	**0.604**	0.000	0.004	**0.292**	**0.082**
Random walk (with drift and GARCH(1,1))	6.800	**1.593**	-1.858	-0.356	**42.786**	2.412	0.521	**0.604**	0.035	**0.107**	0.096	0.005
AR(1) with GARCH(1,1)	6.818	**1.577**	-1.878	-0.381	**42.955**	**2.342**	0.521	0.604	0.011	0.003	0.153	**0.095**
GARCH(1,1) in mean and exogenous predictors	6.978	1.753	-1.122	0.061	47.428	3.070	0.479	0.542	0.004	0.000	0.061	0.001
GARCH(1,1)-in mean and exogenous predictors - t dist.	6.910	1.652	-1.351	0.039	45.923	2.727	0.500	0.521	0.001	0.010	0.102	0.009
EGARCH(1,1)-in mean and exogenous predictors	6.950	1.680	-0.779	-0.177	47.690	2.791	**0.563**	0.563	0.012	0.000	0.061	0.005
EGARCH(1,1)-in mean and exogenous predictors- t dist.	6.915	1.670	-1.022	-0.271	46.769	2.714	0.396	0.583	0.029	0.008	0.051	0.006
TGARCH(1,1)-in mean and exogenous predictors	7.091	1.769	-0.859	-0.049	49.541	3.127	0.354	0.542	**0.083**	0.001	0.004	0.001
TGARCH(1,1)-in mean and exogenous predictors- t dist.	6.944	1.673	-1.010	-0.309	47.193	2.702	0.438	0.563	0.039	0.007	0.034	0.006
Exponential STAR - T-bill	6.791	1.774	**-0.616**	0.081	45.739	3.142	0.438	0.521	0.008	**0.016**	0.196	0.000
Exponential STAR-SRF	7.171	1.681	-0.652	0.049	51.002	2.822	0.417	0.521	0.044	0.004	0.007	0.005
Logistic STAR - T-bill	**6.573**	1.747	**-0.627**	0.055	**42.812**	3.048	**0.604**	0.521	0.023	0.000	**0.609**	0.001
Logistic STAR-SRF	7.459	1.924	0.630	-0.239	55.241	3.645	0.396	0.542	**0.072**	0.002	0.001	0.000
TAR-SR	7.291	1.782	**-0.521**	-0.010	52.889	3.177	0.313	0.521	**0.074**	0.000	0.002	0.000
TAR-SRF	7.081	1.753	-0.887	-0.058	49.351	3.071	0.417	0.479	0.050	0.000	0.010	0.001
Logistic STAR-GARCH(1,1)	6.951	1.747	-0.702	0.055	47.828	3.048	0.354	0.521	0.071	0.000	0.015	0.001
MS Two-state homoskedastic	7.208	1.748	-0.728	0.053	51.428	3.052	0.479	0.521	0.008	0.000	0.013	0.001
MS Two-state heteroskedastic	6.838	1.645	-0.716	-0.160	46.244	2.681	0.458	0.542	0.002	0.000	0.164	**0.014**

2003:02-2007:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	3.525	1.400	0.699	-0.542	**11.936**	1.665	0.667	0.563	0.036	**0.109**	0.296	0.013
Random walk (with drift)	3.536	1.461	0.493	-0.562	12.260	1.819	0.688	0.604	0.021	0.001	0.370	0.025
AR(1)	3.546	1.453	0.478	-0.470	12.343	1.890	0.688	0.604	0.001	0.000	**0.521**	0.033
Random walk (with drift and GARCH(1,1))	**3.509**	1.393	**0.094**	**-0.290**	12.304	1.855	**0.688**	0.604	0.023	0.018	0.503	**0.152**
AR(1) with GARCH(1,1)	3.520	1.392	**0.148**	**-0.285**	12.369	1.856	0.688	0.604	0.004	0.000	**0.667**	**0.238**
GARCH(1,1) in mean and exogenous predictors	3.554	**1.344**	0.290	-0.413	12.545	**1.635**	0.646	0.583	0.020	0.108	0.301	0.086
GARCH(1,1)-in mean and exogenous predictors - t dist.	3.529	1.404	0.312	-0.556	12.359	1.661	0.667	0.604	0.021	0.094	0.404	0.017
EGARCH(1,1)-in mean and exogenous predictors	3.546	1.361	0.385	**-0.335**	12.430	1.740	0.667	0.604	0.020	0.069	0.333	**0.129**
EGARCH(1,1)-in mean and exogenous predictors- t dist.	3.524	1.539	0.335	-0.852	12.303	**1.642**	0.667	0.604	0.023	0.103	0.416	0.000
TGARCH(1,1)-in mean and exogenous predictors	3.547	**1.359**	0.197	-0.450	12.542	**1.644**	0.646	0.583	0.017	0.108	0.353	0.052
TGARCH(1,1)-in mean and exogenous predictors- t dist.	**3.489**	1.490	**0.170**	-0.746	**12.142**	1.663	0.667	0.604	0.030	0.092	**0.552**	0.001
Exponential STAR - T-bill	3.661	1.584	0.261	-0.682	13.333	2.042	0.667	0.604	0.036	0.091	0.052	0.000
Exponential STAR-SRF	3.557	1.408	0.486	-0.555	12.419	1.676	0.646	0.563	**0.041**	0.095	0.173	0.014
Logistic STAR - T-bill	3.647	1.400	0.829	-0.542	12.614	1.665	0.583	0.563	**0.045**	0.109	0.050	0.013
Logistic STAR-SRF	4.565	1.359	0.838	-0.348	20.138	1.725	0.479	**0.667**	0.027	0.101	0.000	0.062
TAR-SR	3.666	1.446	0.615	-0.579	13.059	1.755	0.625	0.625	0.004	0.107	0.103	0.003
TAR-SRF	3.849	**1.346**	0.877	-0.368	14.049	1.677	0.583	**0.688**	0.004	**0.125**	0.011	0.051
Logistic STAR-GARCH(1,1)	**3.517**	1.400	0.674	-0.542	**11.917**	1.665	**0.688**	0.563	0.036	**0.109**	0.327	0.013
MS Two-state homoskedastic	3.545	1.605	0.534	-0.494	12.278	2.332	**0.750**	**0.625**	**0.040**	0.008	0.211	0.000
MS Two-state heteroskedastic	3.699	1.611	0.722	-0.557	13.165	2.286	0.646	0.604	0.010	0.012	0.059	0.000

Panel F: Canada, 1-month Horizon

1995:02-1999:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	5.036	2.198	1.545	0.994	22.972	3.844	0.625	0.500	0.059	0.026	0.082	0.000
Random walk (with drift)	4.952	**1.835**	**0.466**	**0.282**	24.310	**3.286**	0.646	**0.708**	0.043	**0.130**	0.262	0.019
AR(1)	4.932	**1.841**	**0.457**	**0.263**	24.112	3.320	**0.667**	**0.708**	0.003	0.006	**0.820**	**0.361**
Random walk (with drift and GARCH(1,1))	4.962	**1.878**	**0.522**	0.396	24.350	3.369	0.646	**0.708**	0.001	0.030	**0.635**	**0.083**
AR(1) with GARCH(1,1)	4.955	1.883	0.556	0.360	24.238	3.415	0.646	0.708	0.000	0.013	**0.703**	**0.110**
GARCH(1,1) in mean and exogenous predictors	5.110	2.065	1.558	0.414	23.682	4.092	0.542	0.667	0.040	0.124	0.066	0.000
GARCH(1,1)-in mean and exogenous predictors - t dist.	4.896	2.136	1.181	0.514	22.572	4.298	0.542	0.625	0.073	**0.143**	0.214	0.000
EGARCH(1,1)-in mean and exogenous predictors	**4.867**	2.096	0.954	0.600	22.778	4.032	0.604	0.646	0.063	0.095	0.362	0.000
EGARCH(1,1)-in mean and exogenous predictors- t dist.	**4.828**	2.146	0.939	0.684	**22.428**	4.136	0.646	0.604	**0.077**	**0.126**	0.366	0.000
TGARCH(1,1)-in mean and exogenous predictors	4.940	2.204	0.986	0.885	**23.436**	4.073	0.521	0.542	0.046	0.062	0.270	0.000
TGARCH(1,1)-in mean and exogenous predictors- t dist.	4.880	2.174	1.173	0.880	22.439	3.952	0.583	0.521	0.077	0.065	0.225	0.000
Exponential STAR - T-bill	5.701	2.105	2.200	0.480	27.658	4.198	0.646	0.646	0.032	0.001	0.001	0.001
Exponential STAR-SRF	5.039	2.283	1.471	0.674	23.225	4.757	0.625	0.646	0.055	0.025	0.089	0.000
Logistic STAR - T-bill	**4.752**	2.145	0.818	0.662	**21.915**	4.164	**0.688**	0.708	**0.095**	0.008	0.477	0.000
Logistic STAR-SRF	5.127	1.950	1.775	0.511	23.141	3.540	**0.667**	0.646	**0.086**	0.005	0.018	0.027
TAR-SR	5.233	2.121	1.658	0.785	24.640	3.882	0.625	0.583	0.024	0.006	0.032	0.001
TAR-SRF	5.210	2.244	1.611	0.949	24.549	4.136	0.583	0.521	0.030	0.025	0.035	0.000
Logistic STAR-GARCH(1,1)	5.153	2.004	1.204	**0.340**	25.104	3.900	0.625	0.667	0.033	0.046	0.054	0.003
MS Two-state homoskedastic	5.357	2.004	1.356	0.859	26.857	**3.277**	0.500	0.708	0.006	0.037	0.017	0.003
MS Two-state heteroskedastic	5.304	2.006	1.722	0.871	25.169	**3.267**	0.563	0.708	0.005	0.041	0.027	0.003

1999:02-2003:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	4.686	1.719	-0.323	0.220	21.852	2.905	0.583	0.625	0.058	0.004	**0.849**	0.032
Random walk (with drift)	4.861	1.672	-0.690	-0.463	23.151	**2.581**	0.583	0.625	0.000	**0.146**	0.626	0.003
AR(1)	4.834	1.674	-0.643	-0.433	22.951	**2.613**	0.583	0.625	0.010	0.021	0.648	0.073
Random walk (with drift and GARCH(1,1))	4.889	1.647	-0.792	-0.288	23.272	2.630	0.583	0.625	0.003	**0.056**	0.449	0.065
AR(1) with GARCH(1,1)	4.872	1.652	-0.763	-0.283	23.149	2.649	0.583	0.625	0.001	**0.056**	0.553	0.058
GARCH(1,1) in mean and exogenous predictors	4.732	**1.640**	-0.542	-0.119	22.100	2.674	0.542	0.625	0.046	0.000	0.736	**0.303**
GARCH(1,1)-in mean and exogenous predictors - t dist.	4.760	1.664	-0.574	-0.050	22.325	2.767	0.542	0.667	0.038	0.001	0.682	**0.151**
EGARCH(1,1)-in mean and exogenous predictors	4.844	1.670	**-0.032**	**0.022**	23.461	2.788	0.479	**0.688**	0.000	0.001	0.730	0.129
EGARCH(1,1)-in mean and exogenous predictors- t dist.	4.684	1.687	-0.663	-0.044	21.501	2.843	**0.604**	**0.688**	0.080	0.000	0.504	0.083
TGARCH(1,1)-in mean and exogenous predictors	4.846	1.698	**0.041**	0.052	23.486	2.879	0.438	0.625	0.004	0.000	0.662	0.061
TGARCH(1,1)-in mean and exogenous predictors- t dist.	4.747	1.685	-0.686	0.162	22.060	2.811	0.563	0.667	0.047	0.005	0.614	0.078
Exponential STAR - T-bill	4.762	1.771	**-0.057**	0.051	22.669	3.133	**0.604**	0.542	0.073	0.002	0.285	0.009
Exponential STAR-SRF	4.703	1.835	-0.305	**-0.017**	22.021	3.369	0.563	0.542	0.049	0.003	**0.903**	0.002
Logistic STAR - T-bill	**4.624**	1.701	-0.197	-0.042	**21.338**	2.890	0.521	**0.688**	**0.090**	0.002	0.724	0.055
Logistic STAR-SRF	**4.473**	**1.668**	-0.084	**-0.005**	**20.002**	2.782	**0.604**	0.646	**0.149**	0.005	0.694	0.123
TAR-SR	**4.613**	1.750	-0.376	0.200	**21.141**	3.024	0.583	0.604	**0.092**	0.013	**0.748**	0.011
TAR-SRF	4.810	1.755	-0.505	0.192	22.879	3.043	0.542	0.583	0.025	0.019	0.569	0.009
Logistic STAR-GARCH(1,1)	4.764	**1.612**	-0.640	-0.270	22.290	**2.525**	0.521	0.625	0.037	0.023	0.658	**0.394**
MS Two-state homoskedastic	4.946	1.866	-0.281	0.271	24.387	3.407	0.583	0.563	0.009	0.001	0.227	0.001
MS Two-state heteroskedastic	5.063	1.873	-0.808	0.282	24.984	3.427	0.563	0.563	0.001	0.001	0.094	0.001

2003:02-2007:01

Model	RMSFE Stocks	RMSFE Bonds	Bias Stocks	Bias Bonds	Forecast Variance Stocks	Forecast Variance Bonds	Success Ratio Stocks	Success Ratio Bonds	MZ regression (R-square) Stocks	MZ regression (R-square) Bonds	MZ (p-value for intercept =0 and coefficient =1) Stocks	MZ (p-value for intercept =0 and coefficient =1) Bonds
Linear	3.265	**1.405**	0.500	-0.222	10.408	**1.924**	0.542	0.636	0.008	**0.195**	0.002	0.170
Random walk (with drift)	**2.949**	1.557	0.639	-0.386	**8.289**	2.274	**0.729**	0.659	**0.023**	0.006	**0.178**	0.194
AR(1)	**2.948**	1.558	0.592	-0.362	**8.340**	2.295	**0.729**	0.659	0.000	0.003	**0.307**	0.204
Random walk (with drift and GARCH(1,1))	**2.950**	1.514	0.565	**-0.148**	8.381	2.270	**0.729**	0.659	**0.044**	0.002	0.107	**0.759**
AR(1) with GARCH(1,1)	2.968	1.519	0.656	**-0.150**	**8.376**	2.284	0.729	0.659	0.004	0.001	**0.210**	**0.687**
GARCH(1,1) in mean and exogenous predictors	3.304	1.442	0.563	**-0.120**	10.600	2.065	0.583	0.659	0.012	0.108	0.001	0.547
GARCH(1,1)-in mean and exogenous predictors - t dist.	3.204	1.419	**0.355**	-0.160	10.141	1.987	0.688	0.659	0.008	0.150	0.005	0.383
EGARCH(1,1)-in mean and exogenous predictors	3.184	1.477	0.885	0.298	9.357	2.094	0.563	0.636	0.005	0.078	0.008	0.382
EGARCH(1,1)-in mean and exogenous predictors- t dist.	3.198	1.418	0.552	-0.206	9.920	1.969	0.625	0.659	0.008	0.168	0.006	0.235
TGARCH(1,1)-in mean and exogenous predictors	3.194	**1.400**	0.677	-0.162	9.746	**1.934**	0.604	**0.659**	0.005	**0.189**	0.007	0.239
TGARCH(1,1)-in mean and exogenous predictors- t dist.	3.216	1.415	0.369	-0.218	10.209	1.954	0.625	0.659	0.006	0.175	0.005	0.215
Exponential STAR - T-bill	3.103	1.555	0.417	-0.329	9.454	2.309	0.688	0.659	0.001	0.035	0.029	0.104
Exponential STAR-SRF	3.258	1.490	0.458	-0.241	10.406	2.162	0.583	0.614	0.008	0.057	0.003	0.432
Logistic STAR - T-bill	3.224	1.468	0.518	-0.265	10.128	2.086	0.604	0.659	0.007	0.082	0.004	0.460
Logistic STAR-SRF	3.345	1.447	**0.296**	-0.365	11.101	1.960	0.625	**0.682**	0.003	0.161	0.001	0.114
TAR-SR	3.200	**1.356**	0.484	-0.185	10.005	**1.805**	0.583	**0.727**	0.000	**0.210**	0.007	**0.552**
TAR-SRF	3.351	1.450	**0.316**	-0.244	11.132	2.042	0.604	0.659	0.014	0.108	0.001	0.429
Logistic STAR-GARCH(1,1)	3.406	1.439	0.717	-0.212	11.090	2.027	0.521	0.659	0.020	0.122	0.000	0.412
MS Two-state homoskedastic	3.113	1.748	0.430	-0.292	9.505	2.972	0.667	0.682	0.012	0.042	0.019	0.000
MS Two-state heteroskedastic	3.329	1.712	1.167	-0.215	9.723	2.885	0.583	0.659	**0.035**	0.030	0.001	0.001

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

Table 8

Diebold-Mariano Equal Predictive Accuracy Tests: Square vs. Linex Loss Functions

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

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

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

Table 9

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

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		0.870	0.871	0.826	0.729	**0.001**	1.000	0.137	1.000	**0.003**	1.000	0.883	0.414	0.920	0.076	0.926	0.960	0.367	**0.008**	**0.007**
Random walk (with drift)	**0.037**		0.359	0.100	0.107	**0.018**	0.991	**0.032**	0.985	**0.001**	0.984	0.694	0.130	0.534	0.130	0.815	0.948	0.126	**0.003**	**0.003**
AR(1)	**0.049**	0.906		0.153	**0.043**	**0.015**	0.991	**0.039**	0.987	**0.001**	0.985	0.706	0.129	0.556	0.129	0.819	0.949	0.116	**0.002**	**0.002**
Random walk (with drift and GARCH(1,1))	0.129	1.000	0.914		0.167	**0.018**	0.993	**0.049**	0.990	**0.001**	0.988	0.730	0.174	0.609	0.174	0.837	0.951	0.142	**0.003**	**0.002**
AR(1) with GARCH(1,1)	0.185	0.999	1.000	0.882		**0.028**	0.993	0.087	0.993	**0.001**	0.989	0.767	0.271	0.685	0.271	0.853	0.954	0.187	**0.002**	**0.001**
GARCH(1,1) in mean and exogenous predictors	0.997	0.996	0.995	0.988	0.983		1.000	0.606	1.000	**0.011**	1.000	0.976	0.999	0.998	0.999	0.976	0.969	0.953	**0.026**	**0.019**
GARCH(1,1)-in mean and exogenous predictors - t dist.	**0.000**	**0.007**	**0.003**	**0.002**	**0.000**	**0.000**		**0.000**	0.099	**0.000**	0.612	**0.019**	**0.000**	**0.000**	**0.000**	0.112	0.895	**0.003**	**0.001**	**0.001**
EGARCH(1,1)-in mean and exogenous predictors	0.438	0.857	0.825	0.739	0.675	**0.002**	0.998		1.000	**0.001**	0.999	0.952	0.863	0.990	0.863	0.964	0.966	0.756	0.056	**0.035**
EGARCH(1,1)-in mean and exogenous predictors- t dist.	**0.000**	**0.033**	**0.016**	**0.009**	**0.003**	**0.000**	0.936	**0.009**		**0.000**	0.858	0.098	**0.000**	**0.002**	**0.000**	0.307	0.914	**0.003**	**0.000**	**0.001**
TGARCH(1,1)-in mean and exogenous predictors	0.973	0.990	0.988	0.979	0.974	0.748	0.999	1.000	0.998		1.000	0.998	0.997	1.000	0.997	0.995	0.982	0.998	0.317	0.182
TGARCH(1,1)-in mean and exogenous predictors- t dist.	**0.000**	**0.005**	**0.003**	**0.001**	**0.001**	**0.000**	0.427	**0.002**	0.101	**0.001**		**0.025**	**0.000**	**0.002**	**0.000**	0.110	0.893	**0.004**	**0.001**	**0.001**
Exponential STAR - T-bill	0.905	0.981	0.974	0.960	0.941	0.327	1.000	0.875	1.000	0.235	1.000		0.117	0.240	0.117	0.801	0.933	0.140	**0.009**	**0.008**
Exponential STAR-SRF	0.412	0.963	0.951	0.871	0.815	**0.003**	1.000	0.562	1.000	**0.027**	1.000	0.095		0.920	0.584	0.927	0.960	0.367	**0.008**	**0.007**
Logistic STAR - T-bill	0.265	0.840	0.794	0.688	0.599	**0.004**	1.000	0.378	1.000	**0.020**	1.000	0.070	0.265		0.080	0.868	0.951	0.152	**0.006**	**0.006**
Logistic STAR-SRF	0.614	0.963	0.951	0.871	0.815	**0.003**	1.000	0.562	1.000	**0.027**	1.000	0.095	0.589	0.735		0.926	0.960	0.367	**0.008**	**0.007**
TAR-SR	0.697	0.896	0.878	0.838	0.806	0.234	0.999	0.690	0.999	0.190	0.998	0.298	0.697	0.792	0.697		0.918	0.100	**0.008**	**0.009**
TAR-SRF	0.851	0.856	0.855	0.853	0.852	0.843	0.866	0.853	0.864	0.841	0.867	0.843	0.851	0.853	0.851	0.846		**0.039**	**0.014**	**0.013**
Logistic STAR-GARCH(1,1)	0.990	0.998	0.997	0.992	0.990	0.433	1.000	0.953	1.000	0.290	1.000	0.623	0.990	0.979	0.990	0.732	0.158		**0.003**	**0.002**
MS Two-state homoskedastic	**0.000**	**0.001**	**0.001**	**0.000**	**0.000**	**0.000**	0.127	**0.005**	**0.041**	**0.001**	0.110	**0.000**	**0.000**	**0.001**	**0.000**	**0.001**	0.130	**0.000**		0.106
MS Two-state heteroskedastic	0.113	0.327	0.281	0.219	0.172	**0.027**	0.842	0.178	0.736	**0.031**	0.850	**0.023**	0.113	0.193	0.113	0.073	0.142	**0.025**	0.953	

Panel B: Canada, Bond 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		0.852	0.867	0.917	0.790	1.000	0.899	0.893	0.937	0.987	0.922	0.638	0.608	0.398	0.218	0.183	0.437	0.357	0.823	0.863
Random walk (with drift)	**0.001**		0.667	0.777	0.336	0.295	0.207	0.317	0.433	0.324	0.203	0.419	0.386	0.118	0.055	**0.032**	0.225	0.113	0.536	0.625
AR(1)	**0.001**	0.816		0.756	0.308	0.275	0.190	0.301	0.410	0.306	0.184	0.412	0.378	0.114	0.051	**0.031**	0.218	0.103	0.523	0.610
Random walk (with drift and GARCH(1,1))	**0.001**	0.552	0.512		**0.046**	0.167	0.109	0.179	0.147	0.199	0.118	0.373	0.348	0.136	0.074	**0.050**	0.217	0.108	0.418	0.489
AR(1) with GARCH(1,1)	**0.005**	0.551	0.509	0.496		0.395	0.293	0.373	0.601	0.424	0.320	0.476	0.448	0.211	0.119	0.077	0.285	0.159	0.640	0.737
GARCH(1,1) in mean and exogenous predictors	1.000	0.999	0.998	0.999	0.994		**0.021**	0.477	0.757	0.582	0.188	0.523	0.497	0.275	0.120	0.108	0.326	0.198	0.668	0.752
GARCH(1,1)-in mean and exogenous predictors - t dist.	0.581	0.997	0.997	0.998	0.991	0.215		0.668	0.895	0.999	0.789	0.578	0.550	0.339	0.176	0.150	0.385	0.291	0.733	0.825
EGARCH(1,1)-in mean and exogenous predictors	0.998	0.999	0.999	0.999	0.997	0.976	0.992		0.736	0.548	0.402	0.525	0.503	0.304	0.168	0.137	0.342	0.223	0.697	0.778
EGARCH(1,1)-in mean and exogenous predictors- t dist.	0.976	0.998	0.998	0.998	0.995	1.000	0.994	0.176		0.287	0.152	0.449	0.424	0.194	0.093	0.069	0.263	0.144	0.564	0.672
TGARCH(1,1)-in mean and exogenous predictors	0.918	0.997	0.997	0.998	0.991	1.000	0.945	**0.018**	**0.028**		0.087	0.513	0.489	0.276	0.127	0.115	0.327	0.220	0.645	0.745
TGARCH(1,1)-in mean and exogenous predictors- t dist.	0.663	0.998	0.998	0.999	0.994	0.285	0.626	**0.019**	**0.008**	0.141		0.568	0.538	0.303	0.132	0.116	0.358	0.250	0.723	0.799
Exponential STAR - T-bill	0.790	0.978	0.977	0.972	0.977	0.729	0.788	0.515	0.582	0.704	0.782		0.444	0.054	**0.000**	**0.008**	0.101	0.184	0.591	0.603
Exponential STAR-SRF	0.942	0.978	0.978	0.974	0.975	0.934	0.943	0.910	0.888	0.927	0.934	0.948		**0.003**	**0.008**	**0.000**	**0.005**	0.182	0.653	0.627
Logistic STAR - T-bill	0.828	0.981	0.981	0.973	0.970	0.807	0.806	**0.000**	0.430	0.688	0.754	0.372	0.075		0.185	**0.028**	0.569	0.514	0.872	0.812
Logistic STAR-SRF	0.115	0.875	0.875	0.893	0.879	**0.046**	0.094	**0.024**	**0.019**	0.052	0.058	0.062	**0.048**	0.103		0.238	0.909	0.796	0.947	0.886
TAR-SR	0.859	0.971	0.970	0.965	0.967	0.820	0.860	0.686	0.725	0.811	0.851	0.832	**0.031**	0.816	0.939		1.000	0.875	0.986	0.922
TAR-SRF	0.942	0.990	0.990	0.987	0.986	0.910	0.956	0.811	0.868	0.931	0.942	0.763	**0.000**	1.000	0.969	0.488		0.447	0.846	0.754
Logistic STAR-GARCH(1,1)	**0.013**	0.965	0.969	0.907	0.908	**0.010**	**0.028**	**0.004**	**0.011**	**0.019**	**0.020**	**0.043**	**0.031**	**0.029**	0.260	**0.045**	**0.020**		0.969	0.835
MS Two-state homoskedastic	0.250	0.998	0.998	0.995	0.993	0.146	0.249	0.055	0.087	0.166	0.233	0.184	0.085	0.168	0.721	0.150	0.091	0.981		0.568
MS Two-state heteroskedastic	0.491	1.000	1.000	1.000	1.000	0.325	0.461	**0.044**	0.151	0.303	0.420	0.196	0.092	0.242	0.855	0.152	0.086	1.000	0.755	

Note: The table presents p-values for van Dijk and Franses' (2003, DF) test of no differential in predictive accuracy. Boldfaced p-values are below the 5% threshold. In each panel, in cells above (below) the main diagonal we report DF p-values under a weighting function that over-weights forecasts that correspond to returns in the left (right) tail of their empirical distribution, approximated by a Nadaraya-Watson kernel density estimator.

Figure 1

Relative Performance of Linear, ARCH-in Mean and Nonlinear Models Across Countries and Markets

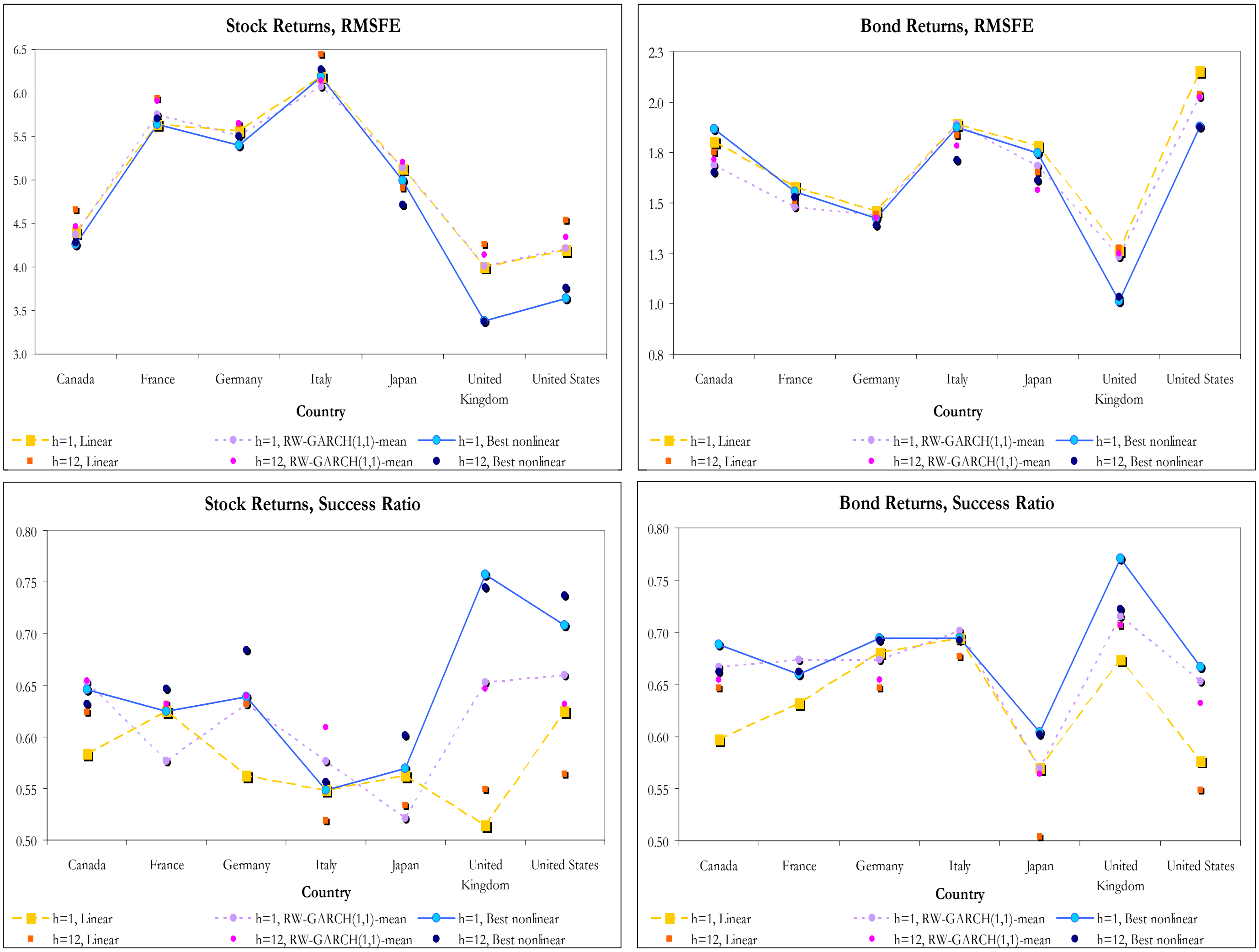

Figure 2

Distribution of Relative Prediction Accuracy Measures over Simulated Data: MSH vs. Random Walk

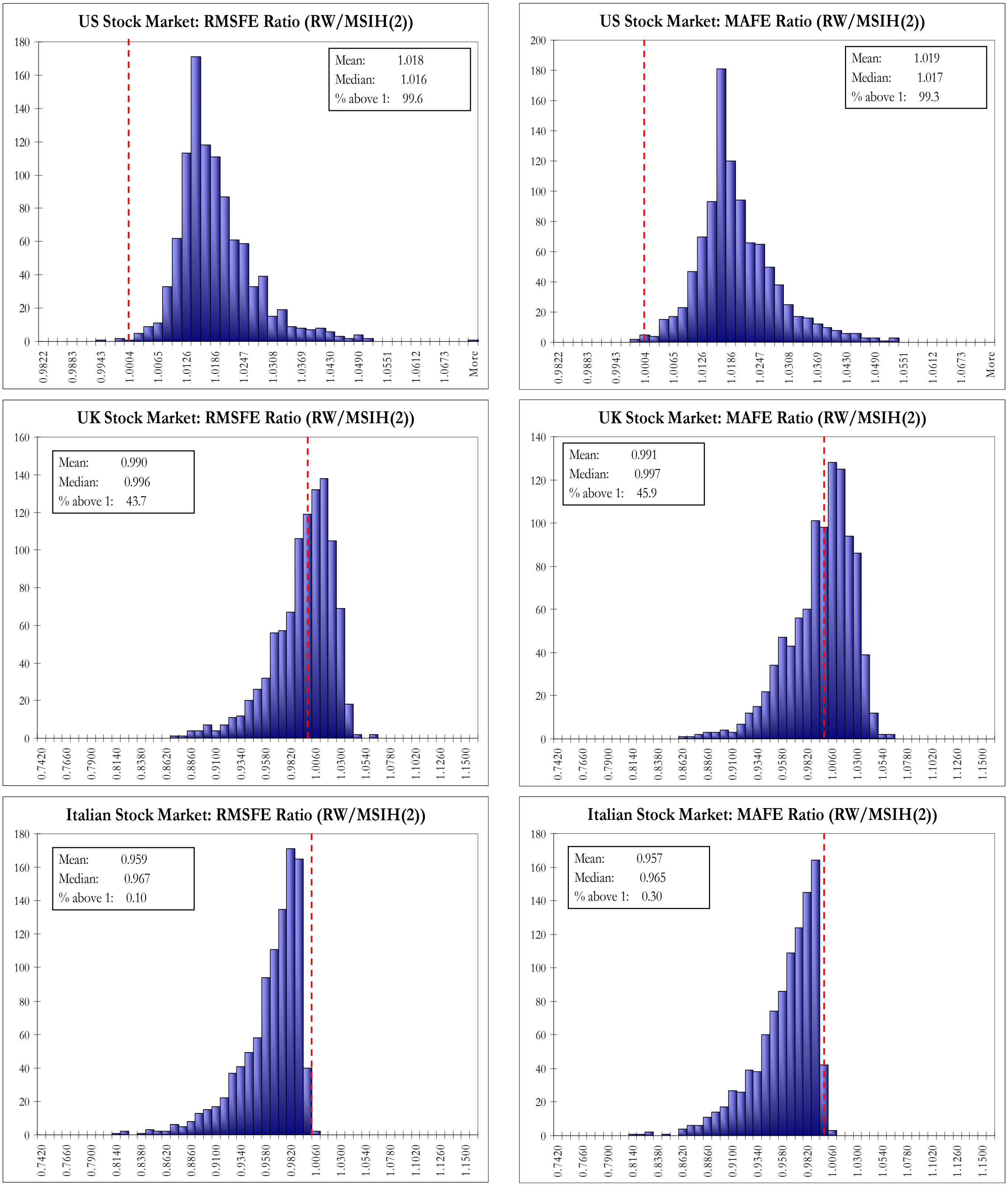

Figure 3

Distribution of Relative Prediction Accuracy Measures over Simulated Data: MSH vs. AR(1) Model