Predicting the future past

How useful is machine learning in economic short-term forecasting?

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Abstract

Many macroeconomic variables are first available when they have already become part of the past. At the same time, there is a large set of figures that is indeed available without the same delay. This thesis use machine learning models to transform real-time data into forecast of future releases about the current and near future state of the economy, asking if such methods produce more accurate forecasts than conventional econometric models. The results indicate that there are no single superior forecasting device. The closest to a 'free lunch' is an unweighted average of the simple benchmark models.

Preface

The past half year have been an exiting one. I am grateful for been given the opportunity to devote so much time in a self-defined project. Sure have I learnt a lot. Some people deserve a special thank you: Ragnar Nymoen, my supervisor, for beeing so interested and for always having his door open. Knowing that one have a living time-series encyclopaedia to ask for help have been a great reassurance for a worried soul as my self. Anne Sofie Jore at Norges Bank for help in retrieving vintage data used in this exercise. Runa, for always ending up explaining me what I try to explain her. Ingeborg, for being the one that never get tired of theoretical discussions, and, of course, for proof-reading a draft of this thesis. O, for allowing me to to run loops on his computer when one was not enough, and for always having a new topic of interest to discuss when he gets tired of the theoretical ones. Thank you.

As well, I owe a debt of gratitude to everyone sharing their problems on the internet and in particular to those providing solutions. This source of knowledge is invaluable.

Most of the data-preparation and estimation has been carried out in **R**, and the codes can be made available upon request. All remaining errors are my own.

Contents

Acronyms

AIC Akaike's information criterion

AR auto-regressive

BIC Bayesian information criterion

CPI consumer price index

CV cross validation

DDD double-difference device

DGP data generating process

DM Diebold-Mariano, refer to the test for equal forecasting accuracy due to Diebold and Mariano (1995)

FFNN Feed forward neural network

GDP gross domestic product

GETS general-to-spesific, refer to GETS-modelling

GUM general unrestricted model

IIS impulse-indicator saturation

k-**NN** *k*-Nearest neigbours

LDGP local data generating process

MDM the modified Diebold-Mariano test proposed in Harvey, Leybourne, and Newbold, 1997

MSE mean squared error

OLS ordinary least squares

QNA Quarterly national accounts

RBF radial basis function

RMSE root-mean-squared error

RNN recurrent neural network

RSS residual sum of squares

RW random walk

SIS step-indicator saturation

SSB Statistics Norway

SVR support vector regression

VAR vector auto-regressive

wk-**NN** weighted *k*-Nearest neigbours

1 Introduction

The aim of this thesis is to compare the performance of machine learning methods, built around prediction, to more conventional econometric forecasting models in providing short-term forecasts of main Norwegian macroeconomic time-series.

While many machine learning models for prediction are not new, they have advanced significantly the last decade, due to the growing amount of data and improved computer capabilities. Their potential as an additional tool in the toolbox of econometricians is addressed by several authors; a heavily cited example is Varian (2014), who provide an early discussion of Big Data and economics. Newer contributions include Mullainathan and Spiess (2017) discussing the the role of machine learning as an (extension of the) data-driven mode of analysis, whereas Athey (forthcoming), Athey and Imbens (2017) focuses on causal interpretation.

A strength of these methods are the ability to use data to build flexible models (Athey, forthcoming; Mullainathan & Spiess, 2017). Typically, they are capable of handling a large set of predictors without *a priori* assumptions on how these data were generated. With that in mind, one may wonder that these methods should be useful tools in short-term forecasting, in making predictions about the current and near future economic conditions, based on the data available at the time? Many macroeconomic variables are first available when they have already became part of the past. The Norwegian Quarterly National Accounts Quarterly national accounts (QNA) is no exception, published about one and a half month after the end of the reference quarter, followed by two years of revisions before considered final. At the same time, there is a large set of figures that is indeed available without the same lag release, including market indexes, surveys and interest rates – as well as newspaper articles (Thorsrud, 2016) and 'new sources' of data such as Google queiries (Varian, 2014).

In this exercise, the short-term horizon is of interest. From *now*, as in the current quarter, through the next four quarters. The targets are the four-quarter change in Mainland Norway gross domestic product and the Norwegian consumer price index.[1] Both univariate and multivariate forecasting models are estimated for both series, assessing to what extent timely information provide better forecast. The forecasts are computed in real-time, meaning that each forecast is made conditional on data available at the time of the forecasting origin, *as if* they were made on that particular point in time. The machine learning forecasts are compared to simpler forecast devices well-known in econometrics, including auto-regressive and vector auto-regressive models for the uni- and multivariate case, respectively. Forecast is computed for the period 2008Q1–2015Q4, which include both one global economic crisis in the years 2008–2009 and one period of

[1]Whereas the GDP is subject to a substantial lag release and repeatedly revision, that is not the case with CPI, published about 10 days after the end of the reference month and not revised.

national economic turbulence due to the sharp decline in oil-prices in 2014. The forecasts are evaluated out-of-sample, in terms of root mean squared forecasting error. The central question asked is whether machine learning methods provide more accurate short-term forecasts – may machine learning methods help to predict the future before it becomes the past?

Now, the notion 'machine learning' may not be very precise, but refer to a set of tools developed in parallel within the fields of statitistics and computer science (James, Witten, Hastie, & Tibshirani, 2013). A formal, yet general, definition of *learning* is provided in T. M. Mitchell (1997, p. 2):

Definition 1.1. A computer program is said to *learn* from experience E with respect to some class of tasks T and performance measure P, if its performance at tasks in T, as measured by P, improves with experience E.

In context of forecasting, the task will be to predict future outcomes. The natural performance measure will be a measure of the accuracy of which the learner produces forecast, and the experience refer simply to the to the estimation sample, to the past. From the definition above it is, however, not easy to say how machine learning differ from other statistical and econometric approaches. Relative to econometrics, Susan Athey argue that the view of empirical analysis as *algorithms* that estimate and compare many alternative models is central to machine learning. In contrast to, she writes, conventional econometric approaches 'where (in principle, though rarely in reality) the model is chosen by the researcher an estimated once' (forthcoming, p. 2). Also Bontempi, Taieb, and Le Borgne argue that these are data-driven models, which use only historical data to learn the 'stochastic dependency between the future and the past' (2013, p. 63). Nevertheless, neither the role of the economic theory nor the econometrician is gone, as any algorithm need to be fed with the right experience, see Mullainathan and Spiess (2017).

Whether or not a new name is necessary for these tools is not discussed here, nor is the difference between machine learning, statistical learning and data mining. This thesis is build on a more pragmatic understanding that all of them refer to a overlapping set of data-driven tools for modelling, in this context for the purpose of prediction. The models or algorithms applied will be referred to as machine learning models, and are popular models both in the statistical learning and machine learning literature, see e.g. James et al., 2013; Hastie, Tibshirani, and Friedman, 2009; Mullainathan and Spiess, 2017; Varian, 2014.[2] All models are forms of *supervised learning*, meaning that they are tools for predicting the unknown outcome of a new observation given a set of conditioning variables. Moreover, they *learn* from a set of such outcome-input pairs, the *training set*

[2]The use of the word 'model' will be used rather sloppy in this thesis; it will refer both to a particluar model subject to estimation and to the different *methods* used to obtain forecasts.

or estimation sample.[3] In contrast, *unsupervised learning* problems consist only of input and no outcome measure – the task of the learner is to find patterns in the data, rather than a predicting the outcome for new observations (Hastie et al., 2009).

The methods implemented include linear, non-linear, parameteric and non-parametric approaches. Against the advantage of theoretically better forecast accuracy, White (2006, p. 467) argue that using non-linear methods has a number of potentially serious disadcantages relative to linear models: (1) the associated estimators can be much more diffucult to compute; (2) flexible non-linear models can easily overfit to the estimation sample, leading to inferior performance in practise; and (3) the resulting forecasts may appear more difficult to interpret. This is indeed true for most of the machine learning methods applied here. These methods does not necessarily include production of good estimates of the parameters β that underlie the relationship between y and $\mathbf{x}$. Even if parameter estimates $\hat{\beta}$ are indeed obtained a part of estimation, these are in general not consistent. Typically, one are not concerned about the form of this relationship f at all, as long as it yields accurate predictions of y (James et al., 2013, chapter 2). The exception that proves the rule in this case is the GETS-algorithm, which aims to find *the* data generating process (DGP). However, as will become clear, when prediction is the goal of modelling, one may want to intentionally estimated a mis-specified representation of the DGP (Castle, Clements, and Hendry (2016), White (2006), see also Shmueli (2011)).[4] That is, the machine learning framework is build around prediction, not inference. Nevertheless, and out of the scope of this thesis, there is an increasing effort in adapting such techniques in this regard as well, see e.g. Athey (forthcoming) for a discussion of the role of machine learning in exploring causal economic relationship.

Similar exercises have been performed, if not with exactly the same models and not with Norwegian data, with mixed results: Garcia, Medeiros, and Vasconcelos (2017) compare a set of high-dimensional econometric and machine learning models, among them the Lasso and random forest which also is applied here, in a real-time forecasting exercise for the Brazilian inflation. They find that using a selecting the 'best' subset of variables is the optimal single approach, but that the average of the models is superior. Kock and Teräsvirta (2016) compare neural networks and GETS models, finding that the linear AR model is hard to beat. In the univariate case, also Teräsvirta, Van Dijk, and Medeiros (2005) find no clear answers in asking wheter or not non-linear models produce

[3]Bontempi et al. provide a complementary notion of supervised learning as, on the basis of a finite set of observations, 'modelling the relation between a set of input variables and one or more output variables, which are considered somewhat dependent on the inputs' (2013, p. 65).

[4]For the remaining methods, even though the exact relationship between y and x remains unknown, there might nevertheless be possible to say something about the *relative importance* of each conditioning variable in predicting y – by looking at the non-zero coefficients from a Lasso-estimation or which variables are the most important split variables in a random forest. This is, however, not done in this exercise.

forecasts that improve upon linear models. In the Norwegian context, Thorsrud (2017) at Norges Bank uses machine learning algorithms to systematize news topics nowcasting the Norwegian GDP, which at sometimes preform even better than the banks official forecasts. Such 'big data' sources is not exploited in this exercise.[5] A contribution outside the field of economics is Caruana and Niculescu-Mizil (2006), who compare supervised learning algorithms for prediction, concluding that the 'No free lunch' theorem holds – no model is best at all tasks.

This thesis proceeds as follows: The next section present all forecasting models applied, starting with an introduction of the concept of *regularization* which is common to most of the machine learning models. Since the methodical aspect is in centre, rather detailed presentations of these models, assumed to be unknown for the reader, follows, before presenting the benchmark models in less detail. Section 3 describe the data and the implementation of the forecasting exercise, in particular with respect to the real-time setting. Also, this section provide details on the estimation of the models, including the required tuning or calibration of hyper-parameters as part of estimation. In section 4 the results from the empirical exercise is presented, before making some considerations of the empirical exercise and providing suggestions for further work in section 5. Section 6 concludes.

[5]Although implicitly through the 'Financial News index' produced by Retriever and Centre for Applied Macro- and Petroleum Economics at BI Norwegian Business School (CAMP). This is a daily index derived from the frequencies of which the Norwegian media writes about various topics, see Thorsrud (2016) The index may be found at https://www.retriever.no/fni/.

2 Forecasting models

2.1 Machine learning models

Before presenting each machine learning method applied in this forecasting exercise, this section intend to briefly introduce the machine learning approach to prediction. In particular, the important idea of *regularization* common to many machine learning methods is introduced. This also suggest a simple taxonomy of the models applied in this exercise.

A supervised learner seeks to produce good predictions $\hat{y}_t$ of the dependent variable y_t, building the model

$$y_t = f(\mathbf{x}_t) + \epsilon_t \tag{2.1}$$

where the n conditioning variables, or *predictors*, constitute the column vector $\mathbf{x}_t = (x_{1t}, x_{2t}, ..., x_{nt})^\top \in \mathbb{X}$ and $\mathbb{X} \subseteq \mathbb{R}^n$ is the predictor space, defined by all possible values for $x_{1t}, ..., x_{nt}$. The random error term ϵ_t is mean zero, such that $f(\mathbf{x})$ is the conditional mean of y given $\mathbf{x}$. The model in (2.1) might be interpreted as the process generating the data at hand. More general, it might be motivated by the observation that, when searching for a function f too produce good predictions of y given $\mathbf{x}$ and 'good' predictions means to minimize the expected squared prediction error, then the solution is given as the conditional mean of y given x (Hastie et al., 2009, chapter 2; White, 2006). Formally, to minimize the expected squared prediction error,

$$E_{(x,y)}E[(y - f(\mathbf{x}))^2] = E_x E_{y|x}[(y - f(\mathbf{x}))^2|\mathbf{x}]$$

it is sufficient to do so point-wise, such that

$$f(\mathbf{x}_t) = \text{argmin}_c \; E_{y|x}[(y_t - c)^2|\mathbf{x}_t] = E[y|\mathbf{x}_t]$$

With reference to Mitchell's definition above, the *task* of the supervised learner is then to estimate the conditional mean of y given $\mathbf{x}$, the regression equation, obtaining a prediction function $\hat{f}$ that can be used to produce predictions of a new observation y_{T+h}. The *experience* refer simply to the estimation sample, a set of pairs $(y_t, \mathbf{x}_t),\ t = 1, ..., T$. The measure of *performance* is again the expected squared prediction error, which may be decomposed as

$$\begin{aligned} E[y - \hat{f}(\mathbf{x})]^2 &= E[(f(\mathbf{x}) - E(\hat{f}(\mathbf{x})) + E(\hat{f}(\mathbf{x})) - \hat{f}(\mathbf{x})]^2 + E[\epsilon^2] \\ &= [f(\mathbf{x}) - E(\hat{f}(\mathbf{x}))]^2 + E[E(\hat{f}(\mathbf{x})) - \hat{f}(\mathbf{x})]^2 + E[\epsilon - E(\epsilon)]^2 \\ &= \text{Bias}(\hat{f}(\mathbf{x})) + \text{Var}(\hat{f}(\mathbf{x})) + \text{Var}(\epsilon) \end{aligned}$$

The variance of the error term is not possible to reduce, thereby providing a lower bound on the expected prediction loss. This variance will be strictly positive all that time there is no perfect deterministic relationship between y and x. The learner should therefore return a prediction function $\hat{f}$ that minimizes the first terms, that has both small bias and low variance. In general, these objectives contradict each other; a prediction function with low bias that fit the estimation sample very well, will typically have high variance, as the fit is likely to change much if estimated on an altered sample. Whereas finding a function either with zero variance (a constant) or zero bias (the line connecting all in-sample observations) is a simple task, the challenge is to find a function that balances this *bias-variance trade-off*.

As a general rule, more flexible methods produce more complex fits with higher variance and lower bias (James et al., 2013, chapter 2). For example, including as many linearly independent regressors as observations in a linear regression, thereby constructing a complex model, will return a R^2 equal to one. That is a perfect fit on the estimation sample, the *in-sample* observations. This fit will have zero bias, yet high variance and will in general not be very generalizable. Hence its potential to predict new observations, observations *out-of sample*, is likely to be poor. This issue, closely connected to the bias-variance trade-off, is refereed to as the problem of *overfitting* and is a central concept in machine learning: The ability to use data to flexibly select functional forms for f is indeed one of the strength of machine learning methods (Athey, forthcoming; Mullainathan & Spiess, 2017). Such flexibility, however, can easily overemphasize patterns in the particular estimation sample. When the goal is prediction, as in the forecasting context, one seeks a model that balances bias and variance, a model that is not *too* complex. This is the idea behind *regularization* techniques, which addresses the problem of overfitting by regulating model complexity. With the intention to increase generalizability and thereby prediction ability, a penalty for complexity is included in the objective function,

$$J(\mathbf{x}, y) = L(f(\mathbf{x}), y) + \lambda R(f) \tag{2.2}$$

where L is the before-penalization (in-sample) loss, often a function of the distance between $\hat{y}$ and y, such as the residual sum of squares (RSS). R is the penalty function that quantifies the complexity of the model f and λ is a regularization parameter determining the degree of penalization, discussed below. In order to minimize this penalized loss function, the gain of increased complexity – reduced bias – must be greater than the associated penalty. In the words of Berk (2016, p. 70) 'the greater complexity has to be worth it'.

The fact that some form of regularization is common to many learning algorithms is useful because it provides a way of thinking about and to conceptually understand them; as constrained minimization problems. Mullainathan and Spiess (2017, p. 93) argue that 'most machine learning might be described in one expression', namely as

$$\min \underbrace{\sum_{t=1}^{T} L(f(\mathbf{x}_t), y_t)}_{\text{in-sample loss}} \text{ over } \overbrace{f \in F}^{\text{function class}} \quad \text{subject to} \quad \underbrace{R(f) \leq s.}_{\text{complexity restriction}} \tag{2.3}$$

where s is the regularization parameter, analogue to λ in (2.2).[6] This representation holds, at least with some goodwill,[7] for all learning models applied in this forecasting exercise and provide a simple taxonomy of these models, presented in Table 2.1.

The estimation problem in (2.3) is solved in two steps: First, conditional on a level of complexity s, the prediction function $\hat{f}$ is given as the function in F that minimizes the in-sample loss. The second step, so far not problematized, is to decide the optimal level of complexity. This means to choose the regularization parameter s, or in the general case parameter$s$, as there might be more than one complexity restriction. These so-called *tuning parameters* should be chosen such that the model, only estimated in-sample, do well at predicting observations out-of-sample. A general approach is to define a set of candidate values for these parameters, estimate the model with each set of parameters, and decide on a final model using the tuning parameters that gave the best performance of the model (Kuhn & Johnson, 2013, chapter 4). Obviously, this approach rely on the ability to obtain trustworthy estimates of the model performance for each value of the tuning parameters. Information criterion, like the Akaike's information criterion (AIC) or the Bayesian information criterion (BIC), are possible analytical solutions to assess predictive performance, well known in econometrics.[8] Such criteria, however, require that the degrees of freedom are well defined. This is not the case for many machine learning methods. More common in this setting is to directly estimate the out-of-sample predictive performance, creating an in-sample experiment: holding out some observations from the estimation sample, the model might be fitted on the remaining observations for each set of parameters, and used to predict the observations held out of estimation. These predictions might then be used to estimate the expected out-of-sample loss for each value

[6]Considering the penalized loss-function in (2.2) as the Lagrangian corresponding to the minimization problem in (2.3), there is for each value of s a corresponding value of λ such that solution to (2.2) is the same as the solution to (2.3)

[7]If willing to accept that the regularizer $R(f)$ is not necessarily a mapping from the function f, in the way it is written here, see Mullainathan and Spiess (2017). More generally, the regularizer might be a set of parameters that restrict the complexity of f rather than a function of f itself, see table 2.1

[8]According to Shmueli (2011), Akaike derived the AIC from a predictive viewpoint; seeking a model intended at predicting future observations as accurately as possible, rather than infer with the 'true' model. This criterion might it self be seen as penalized loss function, as it adjust the in-sample loss by adding a penalty for complexity, measured as the number of free parameters in the model. The penalty induce a trade-off between in-sample fit and model complexity, ie selecting a more complex model should be 'worth it'.

Table 2.1: Overview of supervised learning models.

Function class $\mathcal{F}$ /method	Regularizer $R(f)$
Linear predictors	
Subset selection/GETS	$\sum_{j=1}^{n} \mathbb{1}(\beta_j \neq 0)$
Lasso	$\|\beta\|_{\ell_1} = \sum_{j=1}^{n} \|\beta_j\|$
Ridge	$\|\beta\|_{\ell_2} = \sum_{j=1}^{n} \beta_j^2$
Elastic net	$\alpha\|\beta\|_{\ell_1} + (1-\alpha)\|\beta\|_{\ell_2}$
Local/- non-parametric predictors	
Nearest neighbours	Number of neighbours, k
Random forest	Number of candidate split variables m, number of trees B
Non-linear predictors	
Support vector regression	$\|\beta\|_2 = \sum_{j=1}^{k} \beta_j^2$
Neural networks	Number of hidden layers, number of neurons in each level, connectivity between neurons, weight decay
Combined predictors	
Ensemble: weighted combination of different predictors	Ensemble weights (and individual regularization parameters of each predictor)

Note: Table adapted from Mullainathan and Spiess (2017, table 2, p. 93)

of the regularisation parameters, given for example as the mean squared error (MSE)

$$\text{MSE}(y, \hat{f}(s; x_i)) = \frac{1}{T'} \sum_{i=1}^{T'} (y_i - \hat{f}(s; x_i))^2$$

where T' is the number of held-out observations. The parameters that gave the lowest MSE define the 'optimal' parameters and are used to re-estimate the model on the full estimation sample.[9] Mullainathan and Spiess (2017) denotes this approach *empirical*

[9] Other criteria may as well be used, such as the *one-standard rule* according to which the parameters that results in the *least* complex model within one standard error from the minimum MSE. Note that empirical tuning procedure works because the prediction quality is observable. In contrast, when parameter estimation is the goal of modelling, one rely on assumptions about the data-generating process to ensure consistency, as discussed in Mullainathan and Spiess (2017), Athey (forthcoming).

Algorithm 2.1: Empirical parameter tuning

Input : Set of candidate parameter values
Input : $D_T = \{(\mathbf{x}_t, y_t) : t = 1, 2, ..., T\}$, estimation sample
Output: $\hat{f}(\mathbf{x}_t)$, prediction function
for *each parameter set* **do**
  for *each resample iteration* **do**
    Hold-out specific samples
    [Optional] Pre-process the data
    Fit the model on the remainder
    Predict the hold-out samples
  end
  Calculate the average performance across hold-out predictions
end
Determine the optimal parameter set
Fit the final model f to all training data using the optimal parameter set
return $\hat{f}(\mathbf{x}_t)$

Adapted from Kuhn (2017). See also Kuhn and Johnson (2013, Fig. 4.4)

tuning, which is summarized in algorithm 2.1. Typically, some form of random sampling scheme repeatedly partitioning the estimation sample into training and validation sets is applied in order to increase the number of held-out-observations and thereby obtain a better estimate of the expected predictions loss. Such random re-sampling rely on independently distributed data, which is not unproblematic with the time-series. Therefore an alternative sampling scheme is used in this exercise. In short, a recursive scheme, where the estimation sample expands with one observation for each iteration, is used both to *tune* and to *evaluate* the forecasting models, described in detail in section 3.3.1.

As a simple illustration of regularization, take the choice of lag-length p in the linear auto-regressive (AR) model. The predictors in $\mathbf{x}_t$, including a constant and n lagged observations of the dependent variable y_t, such that $\mathbf{x}_t = (1, y_{t-1}, y_{t-1}, ..., y_{t-n})^\top$, and

$$f(\mathbf{x}_t) = \phi_0 + \phi_1 y_{t-1} + \phi_2 y_{t-2} + ... + \phi_n y_{t-n}$$

Choosing the RSS as the in-sample loss measure, and noting that minimizing over $f \in F$ is equivalent to minimizing over $(\phi_0, \phi) \in \mathbb{R}^{1+n}$, the associated complexity-constrained minimization problem might be written

$$\min_{(\phi_0,\phi)} \underbrace{\sum_{t=1}^{T} \Big(y_t - \phi_0 - \sum_{j=1}^{n} \phi_j y_{t-j}\Big)^2}_{\text{RSS}} \text{ subject to } \sum_{j=1}^{s} \mathbb{1}(\phi_j \neq 0) \leq s.$$

where $\mathbb{1}(A)$ is the indicator function equal to 1 if A is true, zero otherwise. The complexity restriction says that not more than s first lag should have non-zero coefficients.[10] The first step of solving this problem is thus to find coefficients that minimizes the RSS subject to the restriction that at most s lags of the dependent variable should be included in the model, which in this case can be solved by applying ordinary least squares (OLS) to the restricted model. The second step is to estimate the model for all pre-defined candidate values of s. The final AR(p) model is selected as the model with $s = p$ that shows the best predictive performance. As noted above, an econometrician will typically base this decision on an information criteria such as the AIC or some modified version thereof. In contrast, a machine learning practitioner might suggest to repeatedly fit the model on parts of the estimation sample, choosing p as the value that shows the lowest MSE in predicting the hold-out observations. In the more general case, where the n regressors in $\mathbf{x}$ may include other variables than lags of the dependent variable, considering all the $\binom{n}{s}$ possible models for each value of s might be computationally infeasible. Both the GETS-algorithm presented in section 2.1.2 and the penalized regression models presented in section 2.1.1 may be interpreted as computationally feasible alternatives to solve this problem. Where the first starting with the unrestricted model before removing variables one-by-one along multiple paths, the latter restricts the overall size of the coefficients, rather than the number of non-zero coefficients.

The next sections presents the machine learning methods applied in this exercise, starting with maybe the most straightforward implementation of regularization, namely penalized regression. Details on how these methods are applied in the forecasting exercise is saved for section 3.

2.1.1 Penalized regression

Penalized regression is a straightforward application of regularization. This class of methods assumes the same linear functional form of f as in least squares regression, that is

$$f(\mathbf{x}) = \beta_0 + \mathbf{x}^\top \beta,$$

but the estimated coefficients $(\hat{\beta}_0, \hat{\beta})$ minimizes the RSS subject to a complexity constraint,

[10] Note that in this case, the penalty term does not necessarily introduce bias in the model. Under the assumption that y_t is independent of the residual given the lags on the right hand side, the OLS estimates are consistent (yet, biased in finite samples). In a finite sample, however, a more complex model including all n lags will increase the parameter uncertainty thereby the variance of the estimated relationship.

$$(\hat{\beta}_0, \hat{\beta})_s = \underset{\beta_0, \beta}{\operatorname{argmin}} \underbrace{\sum_{t=1}^{T} \left(y - \beta_0 - \mathbf{x}^\top \beta\right)^2}_{\text{RSS}} \quad \text{subject to } R(f) \leq s. \tag{2.4}$$

where s is a regularization constant. The penalized regression models applied in this exercise, namely *ridge regression* (Hoerl & Kennard, 1970), *the lasso* (Tibshirani, 1996) and the *elastic net* (Zou & Hastie, 2005), are characterized by their constraints. That is, they are associated with different regularizers or penalty functions $R(f)$, given as

Ridge: $R^{\text{ridge}}(f) = \sum_{j=1}^{k} \beta_j^2 = \|\beta\|_{\ell_2}^2$

Lasso: $R^{\text{lasso}}(f) = \sum_{j=1}^{k} |\beta_j| = \|\beta\|_{\ell_1}$

Elastic net:[11] $R_\alpha^{\text{elnet}}(f) = \alpha\|\beta\|_{\ell_2} + (1-\alpha)\|\beta\|_{\ell_1}, \quad \alpha \in (0,1)$

Here $\|\beta\|_{\ell_p}$ refer to the ℓ_p-norm or of the coefficient vector β, which for each value of p represent different measures of the distance from at vector to the origin. The ℓ_p-norm, which will appear in more of the models presented below, might be understood as a special case of the *Minkowski distance* between two vectors β and β', given as

$$\left(\sum_{j=1}^{n} |\beta - \beta'|^p\right)^{\frac{1}{p}} = \|\beta - \beta'\|_{\ell_p}, \quad p > 0$$

For $p = 2$ this is the Euclidean distance (the straight line) between the two points, for $p = 1$ is equal to the so-called Manhattan-distance (Kuhn & Johnson, 2013). The ℓ_p-norm is thus equal to the Minkowski distance between β and $\beta' = 0$, ie the distance from β to the origin.

Hence, penalized regression-coefficients are restricted to lie within a certain distance from the origin, and this distance is regulated by the regularization constant s. The case with only two coefficients β_1, β_2 in the coefficient vector β is illustrated in figure 2.1. The black curves in the figure represent combinations of the two coefficients for which the RSS is constant, centred around the unconstrained OLS solution. The different constraints define sets around origo (filled black in the figure), and the intersect between these sets and the RSS-curves are the solution to the constrained minimimization problem in 2.4, which characterizes the penalized regression-coefficients. In the figure, all these coefficients are smaller than what would be the case if there was no restriction. This illustrates

[11] Note that the elastic net penalty is a weighted average of the ridge and lasso penalty, as discussed below.

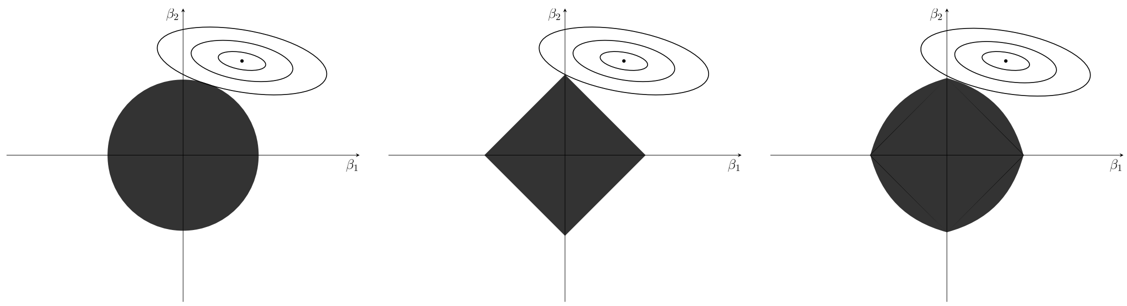

Figure 2.1: Penalized regression as constrained minimization problems. *Left:* Ridge $\beta_1^2 + \beta_2^2 \leq s$. *Centre:* Lasso $|\beta_1| + |\beta_2| \leq s$. *Right:* Elastic Net $\alpha\|\beta\|_{\ell_2} + (1-\alpha)\|\beta\|_{\ell_1} \leq s$. The two shrinkage coefficients is constrained to lie within a set around origo defined by the different penalty functions, illustrated by the coloured shapes. The curves represent combination of the two coefficients for which the RSS is constant, centred around the unconstrained least square solution.

that these coefficients are in general not consistent (assuming the OLS coefficients are). Obviously, if the OLS solution instead were to be found inside the restricted set(s), there would be no difference between the OLS and the penalized regression coefficients.

Limiting the size of the coefficients will in general introduce some bias, but also reduce the variance of the prediction model – it will make it *flatter*. Intuitively, if all coefficients β was zero, $\hat{f}$ would be equal to the constant term – a straight line without variance – for any possible $\mathbf{x}$. The complexity constraint induce a trade-off between in-sample fit, that is minimizing the RSS, and model complexity, here quantified by the size of the coefficients. This might become clearer noting that the solution to the constrained problem in (2.4) minimizes the associated Lagrangian,

$$J(\alpha; \beta_0, \beta) = \sum_{t=1}^{T} \left(y - \beta_0 - \mathbf{x}^\top \beta \right)^2 + \lambda R(\alpha; \beta) \tag{2.5}$$

where $\lambda = \lambda(s)$ is the Lagrangian-multiplier and has the role of controlling the level of regularization. The penalty function $R(\alpha; \beta)$ is here written explicitly as a function of β,

$$R(\alpha; \beta) = (1-\alpha)\frac{1}{2}\sum_{j=1}^{k} \beta_j^2 + \alpha \sum_{j=1}^{k} |\beta_j|, \quad \alpha \in [0, 1]$$

and encompasses both the ridge, lasso and elastic net penalty. That is, setting $\alpha = 0$ results in a ridge regression, $\alpha = 1$ in Lasso regression, whereas $\alpha \in (0, 1)$ correspond to the elastic net, with a penalty function equal to the weighted average of the two aforementioned. Since R increases in the size of β, greater coefficients is discouraged: An increase in the coefficients must improve the (in-sample) fit more than the associated penalty – it has to be 'worth it' (Berk, 2016).

Relative to the least square solution, both the ridge and lasso penalty has the effect of 'shrinking' the estimated coefficients towards zero as λ is increasing, as illustrated in figure 2.2. These methods are therefore also referred to as *shrinkage methods*, as in James et al. (2013) and Hastie et al. (2009). However, the ridge penalty will generally not result in coefficients *exactly* equal to zero (unless $\lambda = \infty$, in which case $s = 0$ and only the zero-vector satisfies the constraint in (2.4)). In contrast, this is often the case with the lasso penalty. The two-dimensional case illustrated in figure 2.1 might provide some intuition to this: The circular set defined by the ℓ_2-norm posed on the ridge coefficients will tend to intersect with the RSS-curves at points *away* from the axes, implying that the resulting coefficients are non-zero. In contrast, the Lasso penalty, the ℓ_1-norm, defines a set with corners at each axis.[12] This restriction will typically imply that the solution lies on one of the axes, ie that some of the coefficients are zero. Lasso regression can thus be said to perform variable selection, by setting the coefficients on variables to zero. Therefore, it can also be used to estimate models where the number of predictors n is greater than the number of observations T, setting at least $n - T$ coefficients to zero. Now, while the ability to handle a large number of predictors might be a strength compared to ridge regression, it is shown that when met with highly correlated predictors, the lasso tends to randomly pick one of these and ignore the rest (by setting their respective coefficients to zero) (Friedman, Hastie, & Tibshirani, 2010). In contrast, the ridge penalty shrinks coefficients of correlated predictors toward each other.[13] This is illustrated in the lower panel of figure 2.2. The elastic net (Zou & Hastie, 2005) was proposed as a compromise between the two ; it can set coefficients to zero, with the number of non-zero coefficients monotonically decreasing as α increases from 0 to 1 (ending at the Lasso-solution), but avoid the unpredictable response of lasso in presence of correlated predictors (Friedman et al., 2010).

The ridge estimator has well-defined analytical solutions for given values of $\lambda = [0, \infty)$. In the case with no intercept, denoting the regressor matrix with elements x_{tj} as $\mathbf{X}$, the

[12] Due to all the corners of the ℓ_1-norm, it is also referred to as the Manhattan or taxicab norm, as it is the shortest distance a taxi driver can take from the origin to a particular point in a rectangular street grid (Nicholson, n.d.)

[13] In the case with n perfectly identical predictors, the estimated ridge coefficients would be identical and equal a share $1/n$ of the coefficients if only one single predictor was included. The Lasso, on the other hand, will break down (Friedman et al., 2010) (as would the OLS-estimator, for that sake). The property of handling correlated coefficients was the motive for ridge regression in the first place (Hoerl and Kennard, 1970; in the presence of perfect multicollinearity, $\mathbf{X}^\top\mathbf{X}$ is non-singular and there is no solution to the unconstrained OLS problem. Introducing the penalty term, the matrix to be inverted is the singular matrix $(\mathbf{X}^\top\mathbf{X} + \lambda I)$.

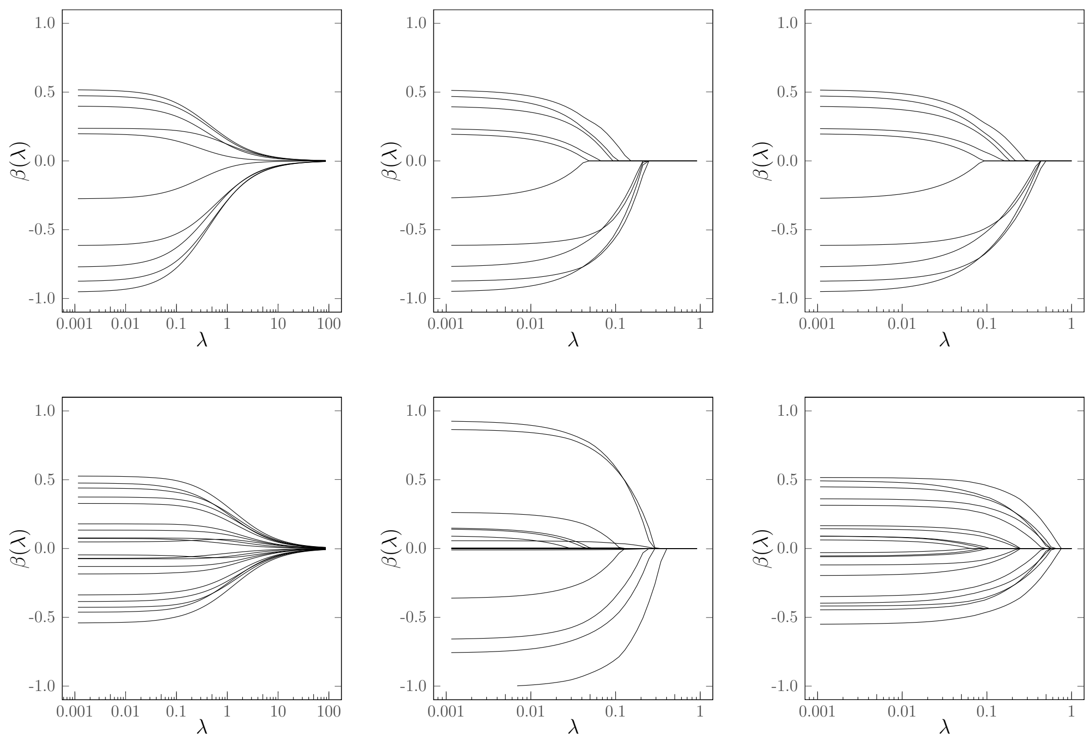

Figure 2.2: Penalized regression coefficients for increasing values of the regularization constant λ (note the log-scale). The true coefficients is between -1 and 1. In the lower panel the set of predictors is expanded by including the same predictors with opposite sign, such that $\mathbf{x}$ include $n/2$ pair of perfectly collinear variables. *Left:* The ridge coefficients are typically shrunken proportionally. In presence of multicollinear variables (lower panel), the magnitude of each coefficient are sare all values $\lambda > 0$. *Centre:* The lasso coefficients is typically shrunken toward zero by a similar amount, and sufficiently small coefficients is shrunken all the way to zero, also when λ is not very high. In presence of multicollinearity, one of the coefficient is set to zero. *Right:* The behaviour of the elastic net coefficients are something in between ($\alpha = 1/2$).

ridge coefficients are given by

$$\begin{aligned}\hat{\beta}^{ridge}(\lambda) &= \text{argmin}_{\beta}\,(y - \mathbf{X}\beta)^{\top}(y - \mathbf{X}\beta) + \lambda I \beta^{\top}\beta \\ &= \left(\mathbf{X}^{\top}\mathbf{X} + \lambda I\right)^{-1}\mathbf{X}^{\top}y,\end{aligned}$$

This is in general not the case for the lasso or elastic net coefficients. Rather, given values of α, λ, these need to be solved for numerically, using some algorithm searching for the minimum of the penalized loss-function in (2.5).[14]

Note that, in contrast to the least squares coefficients, the penalized regression coefficients are scale dependent. Therefore, it might be useful to scale the right hand side variables to have unit variance, in order to not have the solution depend on whether a variable is measured in NOK or in billion NOK say. Also, yet not explicitly commented on, the constant term β_0 is not regularized. The response to changes in $\mathbf{x}$, not the location of $\hat{f}$ should be shrinked. After demeaning all conditioning variables, $\hat{\beta}_0$ is given as the unconditional mean of the dependent variable (James et al., 2013, chapter 6). The standardized variables then are given by

$$\tilde{x}_{tj} = \frac{x_{tj} - \bar{x}_j}{\sqrt{\frac{1}{T}\sum_{t=1}^{T}(x_{tj} - \bar{x}_j)^2}}$$

where $\bar{x}_{tj} = \frac{1}{T}\sum_{t=1}^{T} x_{tj}$, ie they are both *centered* and *scaled*.

Both the regularization parameter λ (or s, equivalently), and the value of α can be determined by fitting the model for a set of candidate values, and choose the value giving the best performance according to a criterion. Hence, estimating three distinct models is not strictly necessary, as the elastic net compromises both Lasso and ridge regression. In this exercise, however, all three models are estimated, for the purpose of comparison. Moreover, contrasting the non-linear models applied in this thesis, it is possible to estimate the degrees of freedom in the penalized regression models, such that information criteria like the AIC might be used to discriminate between different levels of regularization.[15] Section 3 provides the details on the implementation of the empirical exercise, including how these regularization parameters are determined.

As a last note, the three versions of penalized regression introduced in this section might be interpreted as alternatives to the problem of finding the best subset out of of n variables to include in a regression, as in James et al. (2013, chapter 6). This problem might be written

[14] The three penalized regressions models are estimated with the glmnet-package in **R**, which implement a set of cyclical gradient descent algorithms for this task, documented in Friedman et al., 2010.

[15] Zou, Hastie, and Tibshirani (2007), Zou (2005) shows that the number of non-zero coefficients is an unbiased estimate of the degrees of freedom in lasso regression, and provide an more complicated estimator that holds for elastic net regression. The degrees of freedom for ridge regression might be estimated as the trace of the hat matrix, $\mathbf{tr}((\mathbf{X}^{\top}\mathbf{X} + \lambda I)^{-1}\mathbf{X}^{\top})$.

in the same form as (2.4),

$$\min_{\beta_0,\beta} \sum_{t=1}^{T} \big(y - \beta_0 - \sum_{j=0}^{n} \beta_j x_{tj}\big)^2 \quad \text{subject to} \sum_{j=1}^{n} \mathbb{1}(\beta_j \neq 0) \leq s$$

where $\mathbb{1}(A)$ is the indicator function. This problem is computationally infeasible when n is large, as it involve solving up to $\binom{n}{s}$ different models for each candidate value of s. The problem(s) in (2.4) is much easier to solve, due to the simpler constraints, and constitute a computationally feasible alternative. In particular, the lasso and the elastic net which can perform variable selection by setting certain coefficients to zero. The GETS-algorithm presented in the next section might be interpreted as a second alternative to solve the same problem.

2.1.2 General-to-Spesific (GETS) Modelling

General-to-spesific (GETS) modelling represent a strategy for model selection where, starting from the most general feasible model with n variables, statistically insignificant variables or the variables contributing less to the explained variance are removed until a termination criterion is reached – for example that the coefficients of all s retained variables are statistically significant. Such a rule make it computational feasible to solve the problem outlined above: of selecting which s out of n variables to include in the model, as it avoid estimating all possible combinations of s variables among the n. The term GETS is here, however, reserved for the particular multi-path search algorithms following Hoover and Perez (1999) and Hendry and Krolzig (1999) as presented in Hendry and Doornik (2011) and Pretis, Reade, and Sucarrat (2016). This section outline this particular modelling approach, before making some considerations related to the forecasting setting.

The aim of GETS-modelling is to find the *local* data generating process (LDGP). This is the process by which the variables that has been chosen for analysis has been generated, thereby the data generating process (DGP) in the space of these variables (Hendry & Doornik, 2011, chapter 1). The starting point is the formulation of a general unrestricted model (GUM). In the single-equation linear regression setting,

$$y_t = \sum_{j=0}^{n} \gamma_j x_{jt} + u_t \tag{2.6}$$

where n is the number of regressors.[16] Given a chosen set of mis-spesifications tests and

[16] Hendry and Doornik (2011, chapter 21) provide a discussion on selecting non-linear models. Since the potential functional forms of the LDGP is infinite, defining a model general enough to nest such an process might not be feasible. The authors suggests to formulate a polynominal in the k first principal components from the regressors $\mathbf{x}_T$. Only linear models are, however, considered in this exercise.

corresponding significance levels, one should ensure that the general unrestricted model (GUM) does captures the essential characteristics of the data; that it is congruent. In particular, the possibility to locate the LDGP require the GUM be sufficiently general to *nest* this process,

$$y_t = \sum_{j=0}^{k_{\mathrm{LDGP}}} \beta_j x_{jt} + \epsilon_t$$

with $k_{\mathrm{LDGP}} \leq n$. As the LDGP is unknown, the GETS alogrithm search for a specification nested in the GUM (2.6) that contains as many *relevant* variables as possible, and a proportion of *irrelevant* variables corresponding to a chosen significance level α, where a variable x_{jt} is said to be relevant if $\gamma_j \neq 0$, irrelevant otherwise (Pretis et al., 2016, p. 4). This search for relevant variables is done in a multi-path procedure, where variables statistically insignificant are eliminated along paths starting at each of the insignificant variables in the GUM. Eliminating variables along multiple paths allow more combinations of variables to be evaluated than if insignificant variables were moved one by one following a single path. Also, recording which combination of variables that has already been evaluated along one path, the same model is not re-estimated along the next path. This makes it computationally feasible to estimate a large set of the models nested in the unrestricted model, thereby increasing the probability that the 'true' or best approximation of the LDGP is found.

Along each path the validity of each reduction step might be checked against a chosen set of mis-spesification tests, to ensure congruency of the resulting model. If all reductions and diagnostic tests are acceptable and all s retained variables in the model are significant at a particular step, or if further reduction induce mis-spesificaiton, that model becomes the *terminal model* of the given path. Applying a multiple hypothesis test of the validity of the restriction imposed on the coefficients, the terminal models are then tested for parsimonious encompassing against the GUM – whether this smaller terminal model can explain the results of the larger model in which it is nested (Hendry & Doornik, 2011, chapter 1). Should there be several such parsimoniously encompassing terminal models, the final model is selected among these according to a given information criteria. This final model,

$$f(x) = \sum_{j=0}^{k} \delta_j x_j, \quad k \leq n \tag{2.7}$$

is a solution to the problem of selecting which k out of n variables to include in the model, under the additional restrictions that the resulting model should be congruent

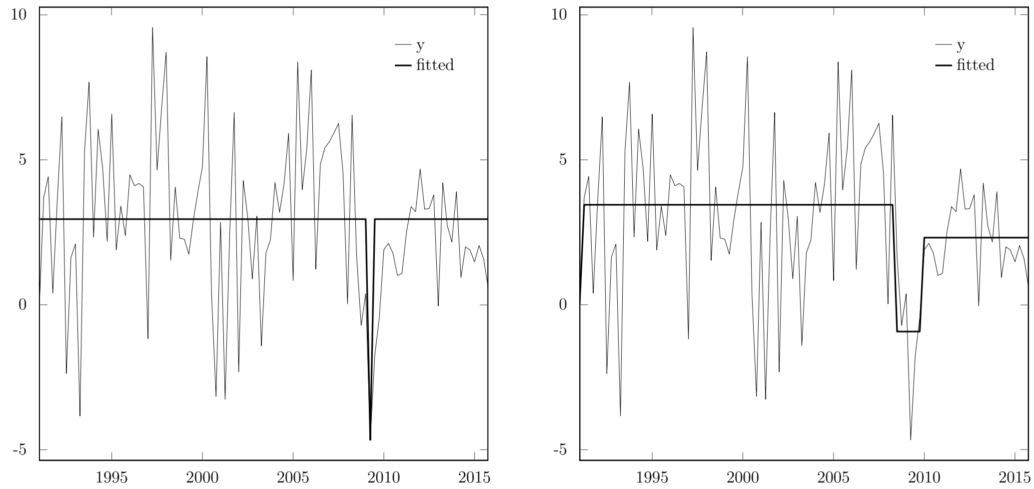

Figure 2.3: Indicator saturation. Regressing the four-quarter change of Norwegian GDP growth on a constant and a full set of indicators. Significant breaks selected with GETS, p-value at 0.01. *Left:* Impulse-indicator saturation (IIS). *Right:* Step-indicator saturation (SIS).

with respect to the (local) LDGP.

The number of retained variables k is chosen as a part of the algorithm, and depend on the level of significance α chosen for the independent tests for relevance along each path. A higher value of α result in less variables being considered irrelevant, thereby keeping more variables in the final model. This increases the rate of which truly irrelevant variables are included in the model. On the other hand, decreasing α will increase the probability of eliminating variables that are truly relevant.

Now, when the goal of modelling is forecasting, in-sample congruency might not be the best target for model selection: Even complete success of locating the LDGP might not improve forecasting if this process is not constant across time – when the relationships between variables that held in the past are ‘a poor basis for making predictions about the future’ (Castle et al., 2016, p. 3). Again, best in-sample is not always consistent with best out-of-sample. A parsimonious model might, however, do better compared to a complex model, as discussed in the introduction to this section. Hendry and Doornik (2011, chapter 23) propose a forecasting approach based on *robustifying* the congruent, parsimonious encompassing model in (2.7) against the most crucial sources for systematic or persistent forecasting failures: to changes in the mean of the included series. Two such strategies is implemented in this exercise, namely *indicator saturation* and *differencing*, presented in the following.

Indicator saturation

The GETS-algorithm can handle more variables than observations, by starting its search for relevant variables in blocks„ before letting the retained variables in each block define a new GUM as the starting point of the search for the final model (Pretis et al., 2016). This allows for the inclusion of a full set of time indicators for in-sample outliers and location shifts in the GUM, denoted impulse-indicator saturation (IIS) and step-indicator saturation (SIS), respectively:

$$\text{IIS:} \quad \sum_{j=1}^{T} \zeta_j \mathbb{1}(t = j), \quad \text{SIS:} \quad \sum_{j=2}^{T} \zeta_j' \mathbb{1}(t \geq j)$$

The GETS-algorithm might then be used to select which indicators that are indeed significant, thereby correcting for shifts in the constant term. Obviously, it is not possible to do so out-of-sample. Also, if one succeed in locating the LDGP, there would be no such shift. Including indicators for outliers and shifts may, however, mitigate some of the adverse effects of mis-specification, all the time one do *not* succeed to locate the LDGP – either because the GUM is underspecified and does not nest this process, or is a poor representation of the potentially non-stationary data generating process for some other reason. In this case, the GUM and hence the final model is mis-specified relative to the (local) DGP, ie not really congruent.

The Double-Difference Device

The IIS and SIS presented above are designed to capture *in-sample* data characteristics, but will not help to predict outliers or location shifts out-of-sample, as demonstrated in Castle et al. (2016). Facing such out-of-sample breaks, differencing is a strategy for robustifying forecast devices. Starting from the notion that most economic time series do not continuously accelerate, one may exploit that whenever a time series y_t is growing at a constant rate its double difference is zero. Thus, the double difference of y_t has zero expectation,

$$E[\Delta^2 y_t] = 0$$

suggesting the simple forecasting rule (Hendry, 2006)

$$\widehat{\Delta y}_{T+h|T+h-1} = \Delta y_{T+h-1} \tag{2.8}$$

which will be unconditionally unbiased. One «key to success» (Hendry, 2006, p. 408) is that all deterministic trends is removed, making this forecast device more *robust* to

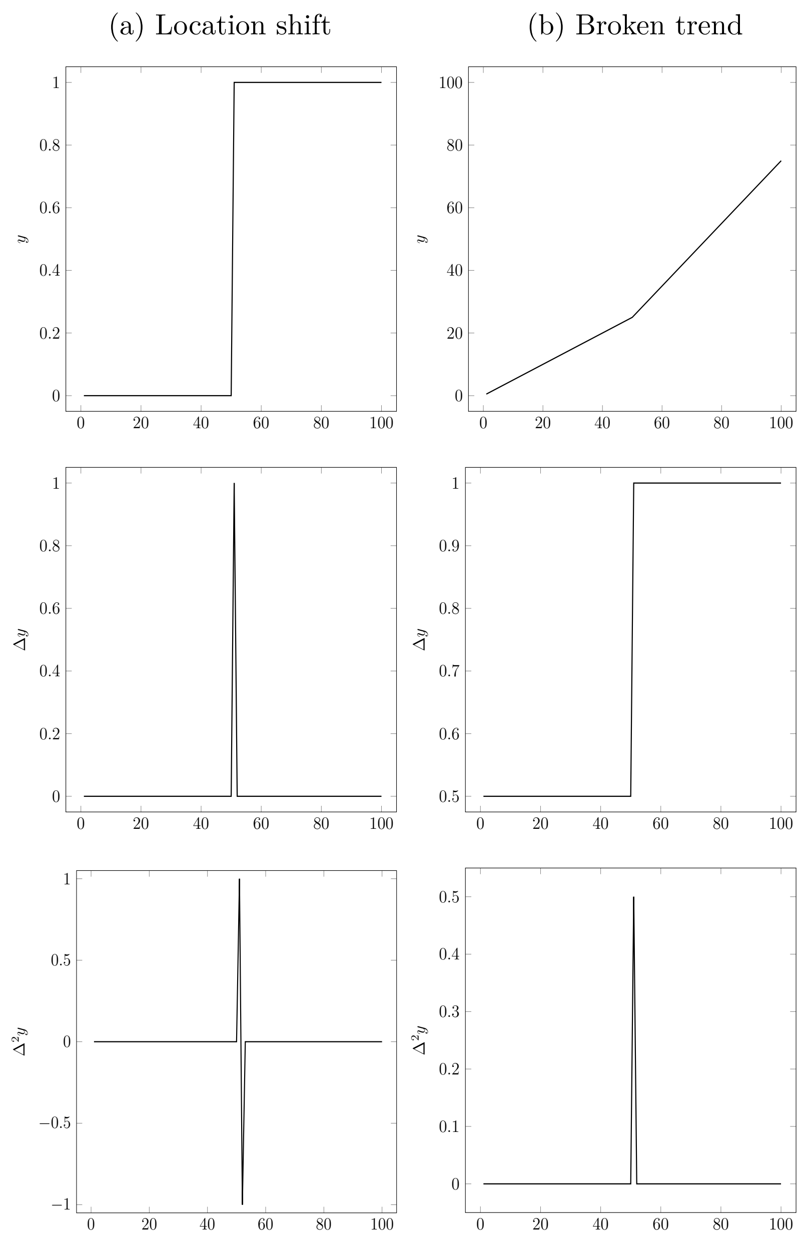

Figure 2.4: First and second differences in the presence of location shift and broken trends. Adapted from Hendry (2006, figure 1., p. 408).

breaks, in the sense that it quickly adapts to such shifts.[17] As illustrated in figure 2.4, in the double-difference of a variable, a change in the mean of this variable in level is visible only as a small 'blip'. A break in the trend of the variable, on the other hand, is seen as a one-time 'jump' in its second difference. Facing such changes in y_t, the one-step ahead forecast obtained by (2.8) will entail a large error in the period of change, but this error will not be persist in subsequent forecast. Yet, the variance of this prediction model will in general be large due to the presence of the differenced term. Applying differences *after* the model in 2.7 has been estimated,

$$\hat{y}_{T+h|T+h-1} = y_{T+h-1} + \sum_{j=0}^{k} \hat{\delta}_j \Delta x_{j,T+h-1} \tag{2.9}$$

will reduce the variance as it does not include the differenced error term $\Delta\eta_t$. This double-difference device exploits the information obtained in constructing parameters $\hat{\delta}$, which hopefully are good approximations to those underlying the data generating process. Of course, with parameters one introduce parameter uncertainty in the prediction model. In particular, it will not be robust to structural breaks in the parameters, rather rely on stability in the estimated coefficients. Nevertheless, it is still robust to location shifts, which according to Hendry (2006) is the most crucial in the forecasting setting. Moreover, it illustrates that models that are deliberaterly mis-spesificed in-sample, might more rapidly adapt to changed circumstances outside the estimation sample (Castle et al., 2016).

2.1.3 k-Nearest Neighbours

The k-Nearest neigbours (k-NN) algorithm is a non-parametric approach based on the simple idea that the unknown outcome value a new observation should be similar to the known outcome for similar observations in the estimation sample. No functional form of f is assumed. Instead, this method intend to estimate the conditional expectation of y directly, as the average outcome for each value of $\mathbf{x}$ (James et al., 2013, chapter 2). In a finite sample it is likely not the case that there is sufficient observations to do so, therefore the conditional expectation is estimated in neighbourhood of a given observation $\mathbf{x}$. Finding the k closest neighbours in the estimation sample, according to a given distance measure, the predicted outcome is simply the average outcome of these k

[17] In a taxanomy of sources to systematic forecast failures, Hendry and Doornik (2011, chapter 23) shows that the double-difference device (DDD) is robust against both location shifts and stochastic breaks, as well as omitted variable bias and parameter uncertainty - simply because there are no parameters to estimate.

observations,

$$\hat{f}(\mathbf{x}') = \frac{1}{k}\sum_{s=1}^{k} w_s \, y_{[s]} \tag{2.10}$$

where w_s is a set of optional weights and $[s]$ denotes the sth closest neighbour to $\mathbf{x}$. The resulting prediction function is locally constant within the neighbourhood $N_k(\mathbf{x})$ of $\mathbf{x}$ defined by its k closest neighbours. Also, it is only defined in this neighbourhoods, and do not represent a global relationship between x and y. The simplicity of this approach is useful also because it it fast to compute: whenever a new set of observations are added to the estimation sample there is no need to re-estimate any model. The new observations simply increase the set of potential neigbours on which new predictions are made (Bontempi et al., 2013; Taieb, 2014)).

The *closeness* of a two vectors $\mathbf{x}, \mathbf{x}' \in \mathbb{X}$ is determined by a given distance metric, for example by the Minkowski distance from section 2.1.1,

$$d(p; \mathbf{x}, \mathbf{x}') = \left(\sum_{j=1}^{n} |x_j - x_j'|^p\right)^{\frac{1}{p}} = \|\mathbf{x} - \mathbf{x}'\|_{\ell_p}, \quad p > 0$$

Again, for $p = 2$ this measure equals the ℓ_2-norm or Euclidian distance, equal to the straight line between the the two points, which is the most popular metric in this use (Kuhn & Johnson, 2013).

The number of neighbours k is here the parameter that control the complexity of the model – a high value of k imply that the prediction $\hat{f}(\mathbf{x})$ is an average of many previous observations $y_{[s]}$, which will hold less variance than an average of only a few observations. At the same time, a high value of k will give high bias as this implies that not-so-close neighbours are included in the estimate. The constrained minimization problem, on the form presented in 2.1, might be written

$$\text{minimize} \quad \frac{1}{T}\sum_{t=1}^{T} \mathbb{1}(\mathbf{x}_t \in N_{k'}(\mathbf{x}_t))(y_t - c_{N_{k'}})^2 \quad \text{subject to} \quad k' = k$$

from which it is obvious that the solution is the average value of y in each neighbourhood.

Weighting the k nearest neighbours according to their distance $d_{[s]}$ from $\mathbf{x}'$ allows the closest neighbours to contribute more to the average in (2.10). The weights w_s might be computed, for example, by applying univariate kernel functions $K(d) \geq 0$ to this distance. These are functions has their maximum for $d = 0$ and decrease monotonously as $d \to \pm\infty$, see the examples given in figure 2.5. Since the distance d is non-negative, only the positive domain of these functions is used. Moreover, it is visible that these

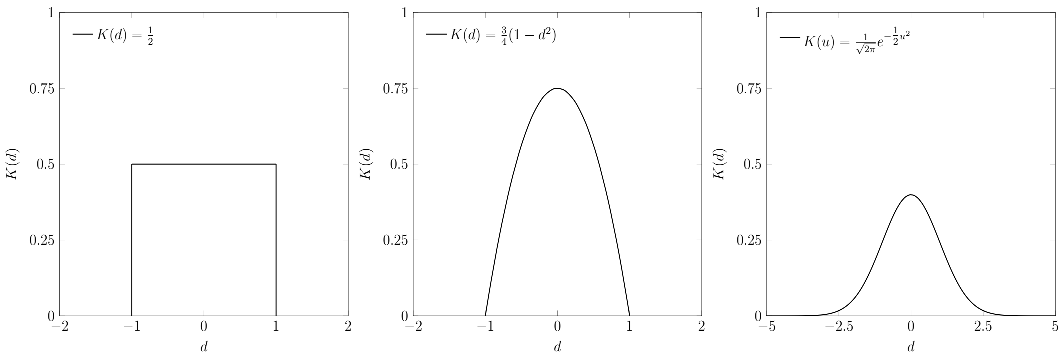

Figure 2.5: Different univariate kernel functions. *Left:* The rectangular kernel. *Center:* The Epanechnikov (parabolic) kernel. *Right:* The Gaussian kernel.

functions might have limited support, that they return values equal to zero for $d \geq 1$. Therefore, in order to avoid weights equal to zero for any of the k closest neighbours, one might standardize the distance relative to the $k+1$ nearest neighbour (Hechenbichler, Schliep, & Wilson, 2004),

$$D(p; \mathbf{x}_{[s]}, \mathbf{x}') = \frac{d(p; \mathbf{x}_{[s]}, \mathbf{x}')}{d(p; \mathbf{x}_{[k+1]}, \mathbf{x}')} \quad s = 1, 2, ..., k$$

such that all distances lies in [0,1]. The algorithm for computing predictions $\hat{y}_{T+h}$ is summarized in Algorithm 2.2.

Algorithm 2.2: k-Nearest neigbours

input : $D_T = \{(\mathbf{x}_t, y_t) \in \mathbb{R}^n \times \mathbb{R} : t = 1, ..., T\}$, estimation sample
input : $\mathbf{x}_{T+h} \in \mathbb{R}^n$
input : k, the number of neigbours
output: $\hat{y}_{T+h}$

for t *= 1, ..., T* **do**
    Compute [for example] the Euclidian distance $d_t = \sqrt{\sum_{j=1}^{n}(x_{tj} - x_{T+h,j})^2}$ from $\mathbf{x}_{T+h}$ to $\mathbf{x}_t$.
end
Sort increasingly the set of vectors $\{\mathbf{x}_t\}$ with respect to d_t.
[Optional] Compute weights w_s by applying a kernel function $K(d)$ to the k smallest distances.

$\hat{y}_{T+h} = \frac{1}{k}\sum_{s=1}^{k} w_s \, y_{[s]}$

return $\hat{y}_{T+h}$

Note: $[s]$ refer to the sth closest neigbour of x_{T+h}.
Adapted from Bontempi, Taieb, and Le Borgne (2013, p. 69).

Because the Minowski distance between $\mathbf{x}, \mathbf{x}'$ depend on the scale of x_j, scaling the inputs might be useful to avoid unreasonably large contributions of high-scale variables, in particular if the inputs are on a very different scale. A more severe issue it that the distance is increasing in the number of predictors n. As discussed by James et al. (2013, chapter 2), if n is large the neighbourhoods are no longer «local». The rate of which $\hat{f}$ approach the conditional expectation of y given x when the sample size increases, $T \to \infty$, is therefore substantially lower. Intuitively, in order to find the k closest neighbours of $\mathbf{x}'$ in the estimation sample, one has to go further away from this points as the dimension n of $\mathbf{x}$ increases. The average outcome of these k observations will be a poor approximation to the expected outcome y given $\mathbf{x}$. In this exercise this instance of the *curse of dimensionality* is addressed by applying k-NN both in multivariate case and in the univariate, where $\mathbf{x}$ only include a restricted number of lags of y.

Finally, the value of k might be chosen by empirical tuning. In essence, this entails to directly estimate the prediction error for each pre-chosen candidate value of k at each end-of sample observation T, before computing the forecast $\hat{y}_{t+h}$ using the value associated with the lowest observed prediction error. The same strategy may be use to select between different distance metrics and different kernels, if any, to compute the weights. The implementation of in the forecasting exercise is described in detail in section 3.

2.1.4 Random forest

Not too different from the nearest neighbour estimator presented above are regression trees. This technique also build a locally constant prediction model, but where k-NN define local relative to each new observation $\mathbf{x}'$, a regression tree is based on a non-overlapping partition of the predictor space $\mathbb{X}$ defined by successively splitting this space in two. Random forest (Breiman, 2001) was proposed as a method to reduce the variance of regression trees, by bootstrap aggregating randomly constructed trees. Since there are no forest without trees, this section will first describe the construction of regression trees, before presenting the idea of bootstrap aggregation, in short *bagging*, and how this may be used to grow a random forest.

A regression tree is a non-parametric model based on a repeated binary partitioning of the predictor space $\mathbb{X}$. The model is often illustrated as a *descision tree*, where successively binary splits of this space constitute the «branches» of the tree and the end-nodes or «leaves» define J distinct and non-overlappping regions, see the leftmost illustration in figure 2.6. The model is a sum of local models, usually just a constant, determined in each region R_j

$$f(\mathbf{x}) = \sum_{j=1}^{J} \mathbb{1}(\mathbf{x} \in R_J) \cdot c_j$$

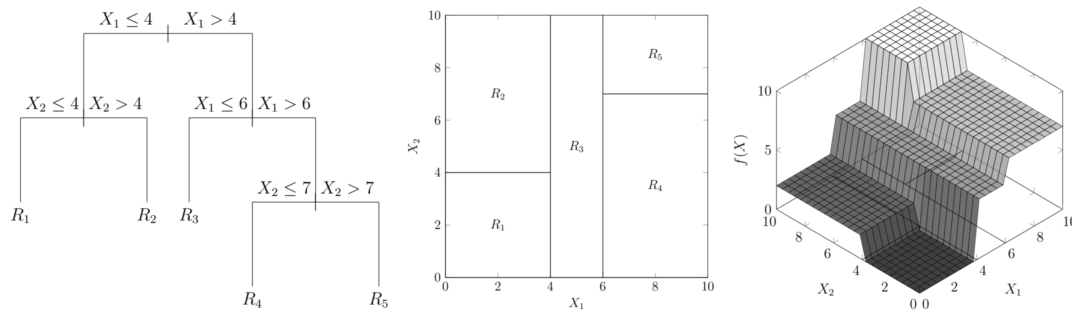

Figure 2.6: A regression tree in the two-dimensional case. *Left:* The recursively binary split illustrated as a tree. *Center:* The resulting partitioning of the predictor space. Each split define two new regions. *Right:* The associated piecewise constant prediction function. Figure adapted from James et al. (2013, figure 9.2, p. 306).

where $\mathbb{1}(A)$ is the indicator function. The function f is thus piecewise constant, implying that the same prediction $\hat{y}_{R_j}$ will be made for each observation falling into region R_j.

In terms of minimum RSS, a feasible partitioning algorithm is the *recursively binary split*.[18] This is an *greedy* algorithm, in that each split is chosen such that the resulting binary partitioning leads to the greatest reduction in RSS at that particular step, without considering that other splits might lead to an overall lower RSS (James et al., 2013, chapter 8). Formally, defining the two regions defined by the line $X_j = s$, as

$$R_i(j,s) = \{X|X_j \leq s\} \quad \text{and} \quad R_{i+1}(j,s) = \{X|X_j > s\},$$

the ith split solves

$$\min_{j,s} \left[\min_{c_i} \sum_{x_t \in R_i} (y_t - c_i)^2 + \min_{c_{i+1}} \sum_{x_t \in R_{i+1}} (y_t - c_{i+1})^2 \right] \tag{2.11}$$

The inner minimization problem is solved by choosing c_i equal to the average value of y_t for the T_i observations in region i,

$$\hat{c}_i = \tfrac{1}{T_i} \sum_{\mathbf{x}_t \in R_i} y_t$$

in direct analog to the nearest neighbour estimator, where the regions are the (potentially overlapping) neighbourhoods.

The tree is grown by successively perform splits at each node as long as there there is more than a minimum number of observations T_{min} in region R_j, or until there is no

[18]As comparing all possible partitionings of the estimation sample might be computional infeasible.

Algorithm 2.3: Random forest

input : $D_T = \{(\mathbf{x}_t, y_t) \in (\mathbb{R}^n \times \mathbb{R})\}$, estimation sample
input : $\mathbf{x}_{T+h} \in \mathbb{R}^n : t = 1, ..., T$
input : m,B, the number of randomly selected split variables and bootstrap samples to draw, respectively
output: $\hat{y}_{T+h}$

Draw B bootstrap samples of the estimation sample.
for b = *1, ..., B* **do**
  Randomly select $m < n$ predic-tors.
  Grow a tree on the bth bootstrap sample using only the m chosen predictors as candidate split variables, to obtain $\hat{f}^{*b}(\mathbf{x}_t)$.
end
$\hat{y}_{T+h} = \frac{1}{B}\sum_{b=1}^{B} \hat{f}^{*b}(\mathbf{x}_{T+h})$
return $\hat{y}_{T+h}$

Note: Adapted from Kuhn (2013, Algorithm 8.2 p. 200)

split that improve the fit (Therneau, Atkinson, & Foundation, 2018). As with the other models presented, overfitting is a central issue in growing regression trees – without any restrictions on the size of the tree, there is a risk that the tree will fit the estimation sample *to* well. For example, if the sample is split into as many regions T as observations, that is $T_{min} = 1$, the tree will perfectly fit the estimation sample. Consequently, the resulting prediction function will have a high variance. Following the concept of regularization, a full-grown tree with J final regions, might be *pruned* back by finding the smallest tree nested in the larger that minimizes the penalized residual sum of squared (James et al., 2013, chapter 8),

$$\text{minimize} \quad \sum_{t=1}^{T}(y_t - \hat{f}(\mathbf{x}_t; J))^2 + c_p \cdot J$$

where $\hat{f}(\mathbf{x}_t; J)$ is written as a function of the number of regions J. Here c_p is the regularization parameter, the cost associated with an additional split. Instead of controlling the size of the tree, the random forest approach intend to reduce the variance and increase the prediction accuracy of regression trees by combining bootstrap aggregation, in short *bagging*, with *random selection* of $m < n$ predictors as candidate split variables.

Bagging is the procedure of averaging predictions from bootstrapped estimations samples, with the intention to reduce the variance of the prediction model. Constructing B bootstrap samples and fitting the model f on each of these samples, the final prediction is given as (James et al., 2013, chapter 8)

$$\hat{f}_{\text{bag}}(\mathbf{x}) = \frac{1}{B}\sum_{b=1}^{B}\hat{f}^{*b}(\mathbf{x})$$

where $\hat{f}^{*b}(\mathbf{x})$ is the fitted model on the bth bootstrap sample. Bagging regression trees, one can allow the trees to grow large without pruning them, meaning that each tree has high variance but low bias, as the the variance of the *final* model will be reduced by averaging. However, if there is strong predictors among the set of conditioning variables, these will likely define the first couple of splits in most of the bagged trees. Hence, the the bagged predictions will be highly correlated, implying that the potential to reduce variance by averaging is lower. Introducing randomness by for each bootstrap sample arbitrary selecting a subset $m < n$ of the regressors as potential split variables, thereby constructing a *random forest*, will reduce the correlation between the trees. The mean across the random forest is less variable compared to the set of trees grown with the same set of split variables. The procedure to obtain the estimate $\hat{y}_{T+h}$ is outlined in algorithm 2.3.

The number of candidate split variables m control the bias-variance trade-off; if m is high, the bootstrap aggregated trees are likely to be similar such that averaging them does not prevent overfitting. On the other hand, if m is low the trees are not correlated and their average will hold less variance, but high bias, as the average then will be close to the unconditional mean of y. Again, this parameter might be determined by empirical tuning.

2.1.5 Neural Networks

Neural networks encompass a large class of models, with different network *architectures*, typically represented by a network diagram, examples of which is given in figure 2.7 and figure 2.10. In essence these are all non-linear statistical models, which also are popular in the economic forecasting literature, see e.g. White (2006), Teräsvirta (2006). This section first introduce the elements common to all networks, before presenting the two particular network architectures applied in this exercise.

A neural network consists of a set of artificial neurons, called *nodes* or *units*, connected with a set of directed edges. Each node j is associated with a transfer function l_j and the edge from j' to j with a weight $w_{jj'}$. The set of nodes, edges and transfer functions constitutes the *architecture* of the network. The value v_j of each node j is given as the value of it's tranfer function evaluated at the weighted sum of it's inputs (Lipton, 2015),

$$v_j = l_j\left(\sum_{j'} w_{jj'} \cdot v_{j'}\right) \tag{2.12}$$

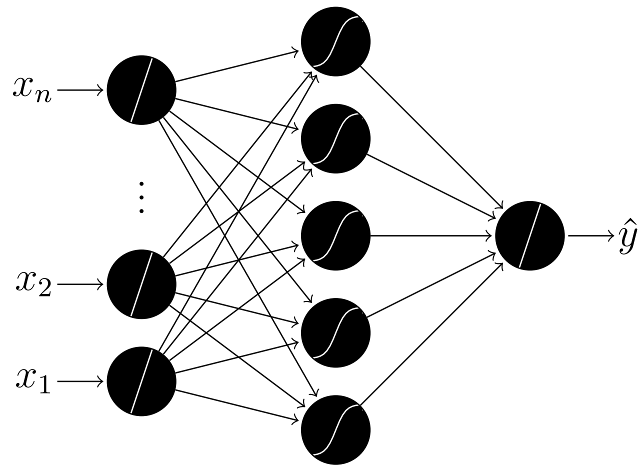

Figure 2.7: Example of a feedforward neural network with one hidden layer. The value of each node in a layer is sent to one or several nodes in the successive layer. The outcome of the network is the value of the single output node. Typically, a *bias node* is added to each hidden layer (not illustrated). The white lines in each node illustrate the transfer function of the respective node, see also figure 2.8.

In the regression case, there is typically one single output node which transfer function is the identity function.[19] The output of the network is then simply a weighted average of the values of the J nodes connected to the output node,

$$f(\mathbf{x}) = \sum_{j=1}^{J} w_j \cdot v_j$$

Thinking of these values v_j as a set of variables derived from the original input vector, a neural network can be seen as a two-stage regression model (Hastie et al., 2009; Kuhn & Johnson, 2013): in the first stage, the regressors are transformed into a new set of variables,

$$v_j = v_j(\mathbf{x}) = l_j \left(\sum_{j'} w_{jj'} \cdot v_{j'}(\mathbf{x}) \right)$$

where $v_j = v_j(\mathbf{x})$ is written as a function of the input to the network, $\mathbf{x}$, even though there might not be any *direct* connection between the input and node j. In the second stage, these new variables constitute the right hand side variables in the final regression.[20]

[19] However, as well multiple quantitative responses $y_{it}, i = 1, ..., K$ might be predicted from a single network, in which case there would be K output units in the network.

[20] These variables are, however, latent - they are the values of *hidden* nodes and is not observed.

For convenience, denoting the jth weight as β_j,

$$f(\mathbf{x}) = \beta_0 + \sum_{j=1}^{J-1} \beta_j \cdot v_j(\mathbf{x}) \tag{2.13}$$

where β_0 is the weight on a so-called *bias node* with value equal to one, analog to the constant term in ordinary regression. This model is linear in β and the derived features v_j, but not in $\mathbf{x}$. By introducing non-linear transformations of the predictors, neural networks greatly enlarges the class of linear models described by (2.13). For certain architectures the neural network is said to be an *universal approximator*: As shown in Hornik, Stinchcombe, and White (1989), among others, there exist a finite number J any measurable function $g(\mathbf{x})$ might be approximated as the linear combination $\sum_{j=1}^{J} \beta_j \cdot l(\sum_{j'} w_{jj'} x_{j'})$, where $l(z)$ is a non-decreasing function satisfying $\lim_{z\to\infty} l(z) = 1$ and $\lim_{z\to-\infty} = 0$. This is simply the model in (2.13) whenever $v_j(\mathbf{x}) = l(\sum_{j=1}^{J} w_{jj'} x_{j'})$, as in the single-layer feed forward network presented below.

One transfer function satisfying the conditions above is the sigmoid function $\sigma(z)$, which is a popular choice for the hidden units. Another popular choice is the hyperbolic tangent function $\tanh(z)$ (Lipton, 2015)

$$\sigma(z) = \frac{1}{1+e^{-z}}, \qquad \tanh(z) = \frac{e^z - e^{-z}}{e^z + e^{-z}}$$

Both these functions has the desirable property of being non-linear, non-decreasing and continuously differentiable (the last property useful it optimization, as discussed below). The range of these functions are $(0, 1)$ and $(-1, 1)$, respectively. Moreover, they produce values close to these boundaries over most of the domain and close to linear around zero, see Figure 2.8.[21] For values close to zero, however, these activation functions are almost linear. Hence the network collapses into an approximately linear model when the weights are very small (Hastie et al., 2009).

The weights are the parameters of a neural network. These are chosen to minimize a loss function, typically the residual sum of squares in the case of regression (Hastie et al., 2009, chapter 11). Obviously, the number of weights that need to be estimated increases in the number of nodes. If there are many weights relative to the number of observations, the weights minimizing the loss network is likely to result in an overfitted model. In order regularize the complexity of the network, one may add a penalty increasing in the

[21]The value of the hidden nodes is thus «high» or «low», «on» or «off», therefore these functions is often referred to as *activation functions* and the value of each node as it's *activation*.

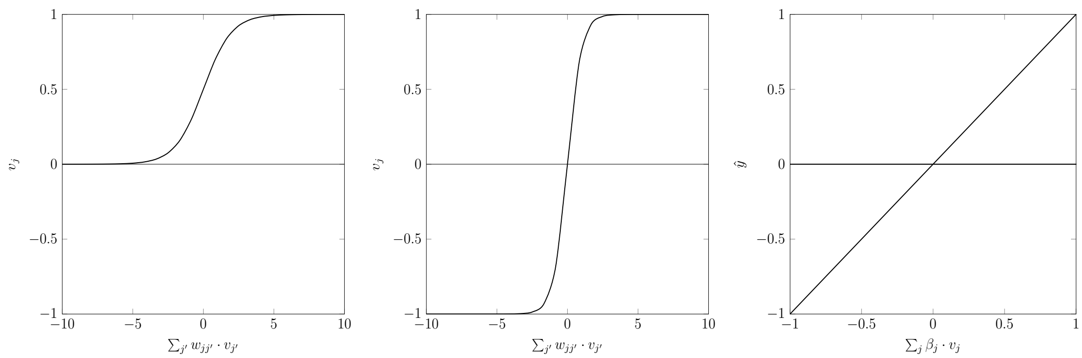

Figure 2.8: Different transfer functions. *Left:* The sigmoid function. *Center:* The hyperbolic tangent function. *Right:* The identity function, the transfer function of the output node.

magnitude of the weight-vector w in the loss function, minimizing

$$\sum_{t=1}^{T}(y_t - f(\mathbf{x_t}; w))^2 + \lambda \|w\|_{\ell_2}$$

where λ again is a tuning parameter regulating the level of regularization.

This minimization problem needs to be solved numerically. The weights are usually initialized with random values close to zero before iteratively updated according to the rule of some learning algorithm. Hence the model starts out nearly linear, before non-linearities are introduced by increasing the weights where needed. One commonly used algorithm for obtaining weights is backpropagation, described in detail in Günther and Fritsch (2010) and Lipton (2015), among others. In essence, at each iteration the gradient of the loss function is calculated using the chain rule, as the value of each node is a function of the weights (and the associated inputs). The weights is then modified going in the opposite direction of their partial derivatives, until a (local) minimum or some convergence criteria is reached. Variants of backpropagation follows different rules with respect to by how much the weights should be change at each iteration. If the loss-surface is non-convex, however, it is not sure that these algorithms will reach a global-minimum. The resulting weights of the network will in that case be sub-optimal. One way to reduce the instability of the networks resulting from such sub-optima is to train multiple networks with different initial weights, and average predictions from all these network (Kuhn & Johnson, 2013, chapter 7)

The following present the network architectures applied in this exercise: a one-layer feed forward network and the simple recurrent Elman (1990) network.

Feedforward Neural Networks

Feed forward neural network (FFNN) is a class of networks where all the cells are arranged in successive layers, and the output of each layer can be calculated given the outputs from

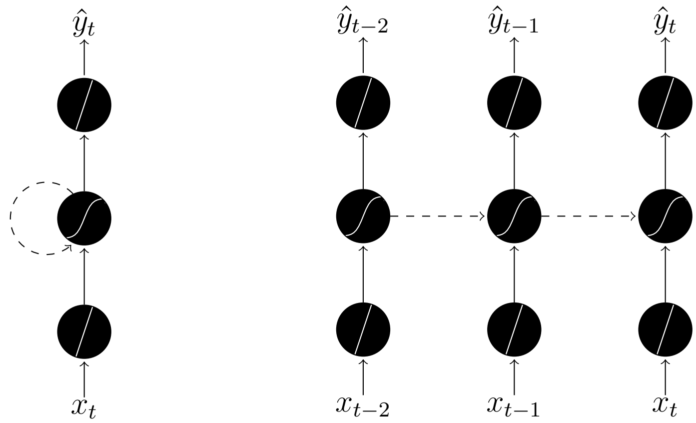

Figure 2.9: A simple recurrent neural network. *Left:* The hidden node in the network is connected with it self by an temporal edge (dashed). *Right:* The *unfolded* network shows the dynamics across time. The input to the hidden node at time t is the current network input x_t and it's activation at $t-1$. More general, the illustratred input and output nodes might refer to the input and hidden layers.

the lower layers (Lipton, 2015). That is, output is only sent, or *fed*, forward, as illustrated in figure 2.7. The input $\mathbf{x}$ to such a network determine the number of and the value of each cell in the first layer, called the *input layer*. The topmost layer is the *output layer*, consisting of one single node which value is the predicted outcome. In between these two, there might be one or several layers with hidden nodes, referred to as *hidden layers*.

The simplest feed forward network is the one without any hidden layer, consisting only of one input layer, and one output node. Adding a so-called *bias node* with value equal to 1 to the n nodes in the input layer, the outcome of the network is simply the linear regression model

$$\hat{f}(\mathbf{x}) = \hat{\alpha}_0 + \sum_{j=1}^{n} \hat{\alpha}_j \cdot x_j$$

Adding hidden layers will increase the modelling flexibility. For example, with one single hidden layer with $J+1$ hidden nodes, the output of the network would be

$$\begin{aligned}\hat{f}(\mathbf{x}) &= \hat{\beta}_0 + \sum_{j=1}^{J} \hat{\beta}_j \cdot v_j \\ &= \hat{\beta}_0 + \sum_{j=1}^{J} \hat{\beta}_j \cdot l_j\Big(\hat{\alpha}'_0 + \sum_{j'=1}^{n} \hat{\alpha}'_{jj'} x_{j'}\Big)\end{aligned}$$

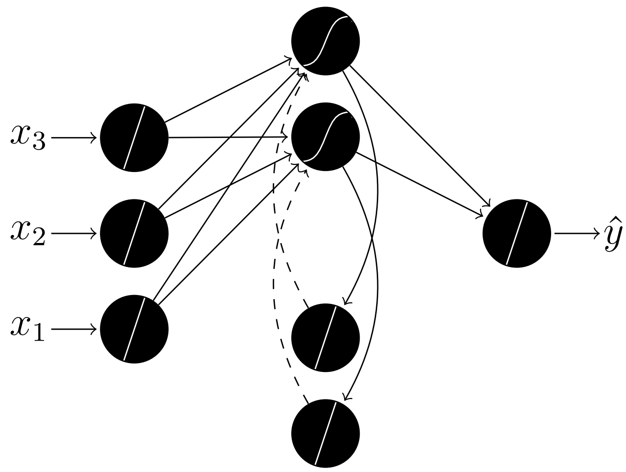

Figure 2.10: The Elman 1990 network. The activation from each node in the hidden layer is sent forward to the output node and to a context unit, which feed this activation back into the same hidden node at the next time step (along the dashed line).

where the marked α' is meant to indicate that the weights in the latter network is not the same as in the former.

Recurrent Neural Network

Recurrent neural network (RNN) is a set of feed forward networks augmented with edges between nodes that span *across time* (Lipton, 2015). There are many different RNN architectures. In the simplest case, each node j in a single hidden layer is connected with it self across time. At each time t each node receives as input a weighted sum of both the current network input $\mathbf{x}_t$, *and* its own activation $v_{j,t-1}$ in the last period, as illustrated figure 2.9. The value of the jth node is then given by

$$v_{jt} = l_j \left(\sum_{j'} w_{jj'} \cdot x_{j't} + w_{jj} \cdot v_{j,t-1} \right) \tag{2.14}$$

where w_{jj} is the weight associated with the edge from the jth to it self.

The temporal connections does not need to be within the hidden layer. In the recurrent network explored in this exercise, the Elman (1990) network, this is, however, the case.[22] In this network there is for each hidden unit an additional hidden unit called *context units*. The jth context units receives as input the (unweighted) activation v_{jt} from the jth node in the hidden layer. At the next time step, at time $t+1$, this activation is fed into the same node, as illustrated in figure 2.10. These context units might be thought

[22]Elman proposed this network as a simplification of the Jordan (1986) network, where indeed there is the value of the output nodes that is fed back into the hidden layer at the next time step. The Elman network is also known as the *simple recurrent network* (Mcclelland, 2015).

of as internal state variables for the network. Since there is one context unit associated with each node in the hidden layer and the connection between them are one-to-one, this set-up is equivalent to the case above where each hidden node is self-connected. The value at time t of each hidden node in the Elman network is therefore given as (2.14).

2.1.6 Support Vector Regression

Support vector regression (SVR) is an extension of the support vector *machines* originally developed for classification in the mid-1960s by Vladimir Vapnik (Kuhn & Johnson, 2013, chapter 7). In the regression context this class of modelling techniques represent a flexible and robust approach, where one seek to minimize the effect of outliers. The particular support vector regression approach presented and implemented in this thesis is referred to as the ϵ-insensitive regression. This section present this modelling approach, starting with the linear case, before introducing the *kernel trick* which allow for a simple way to estimate complex non-linear models.

The goal of SVR is to find a function $f(\mathbf{x}_t)$ as *flat* as possible, that deviates at most ϵ from the associated output values y_t (Smola & Sc Olkopf, 2004). In the linear case, this function is on the form

$$f(\mathbf{x}) = \beta_0 + \mathbf{x}^\top \beta$$

The desired flatness, or lack of complexity, refer to minimize the magnitude of β, the ℓ_2-norm presented in section 2.1.1. The associated minimization problem might be written

$$\underset{\beta_0,\beta}{\text{minimize}} \ \ \tfrac{1}{2}\sum_{j=1}^{k}\beta_j^2 \quad \text{subject to} \quad \begin{cases} y_t - \mathbf{x}_t^\top\beta - \beta_0 \leq \epsilon \\ \mathbf{x}_t^\top\beta + \beta_0 - y_t \leq \epsilon \end{cases}$$

Now, this problem is not guaranteed to have a solution – there might not exist a vector $\hat{\beta}$ such that $\hat{f}$ approximates y with ϵ precision. In order to make the optimization problem feasible, one can allow $f(x)$ to deviate more than ϵ from y by introduce slack variables ξ_t, ξ_t^*. These take positive values whenever $|f(\mathbf{x}_t) - y| - \epsilon$ is greater than zero, as shown in the centre illustration of figure 2.11. The minimization problem is then given as

$$\begin{aligned} &\underset{\beta_0,\beta,\xi_t,\xi_t^*}{\text{minimize}} \ \ \tfrac{1}{2}\sum_{j=1}^{n}\beta_j^2 + C\sum_{t=1}^{T}(\xi_t - \xi_t^*) \\ &\text{subject to} \quad \begin{cases} y_t - \mathbf{x}_t^\top\beta - \beta_0 \leq \epsilon + \xi_t \\ \mathbf{x}_t^\top\beta + \beta_0 - y_t \leq \epsilon + \xi_t^* \\ \xi_t, \xi_t^* \geq 0 \end{cases} \end{aligned} \tag{2.15}$$

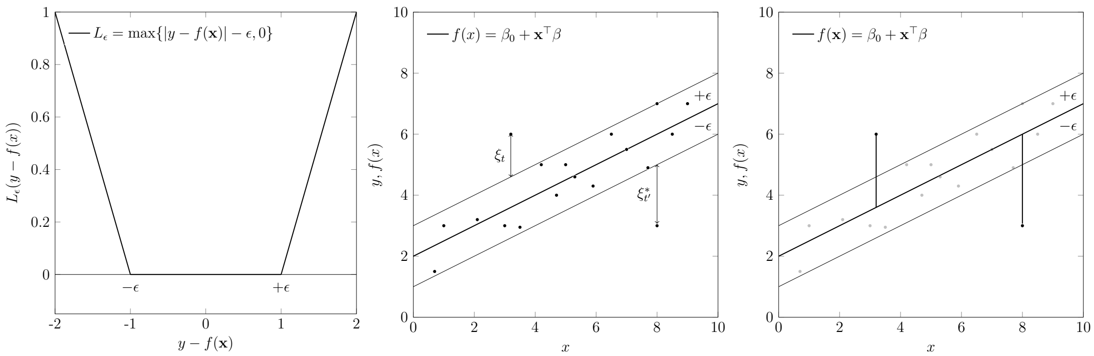

Figure 2.11: Vapnik's ϵ-insensitive loss function and the linear regression line. *Left:* The ϵ-insensitive loss function with $\epsilon = 1$. *Center:* The slack variables allows deviation larger than ϵ. *Right:* The resulting *support vectors* define the regression line.

The constant C has the role of controlling the complexity of the fit; the greater C the higher cost is associated with deviations larger than ϵ. Hence, for higher values of C the fit will be more complex, less flat. More comprehensibly, the problem is to minimize

$$J = \frac{1}{2} \|\beta\|_{\ell_2}^2 + C L_\epsilon(y - f(\mathbf{x})) \tag{2.16}$$

where $L_\epsilon(\cdot)$ is is Vapnik's ϵ-insensitive loss function (Smola & Sc Olkopf, 2004),

$$L_\epsilon(y - f(\mathbf{x})) = \begin{cases} 0 & \text{if } |y - f(\mathbf{x})| \le \epsilon \\ |y - f(\mathbf{x})| & \text{otherwise} \end{cases}$$

plotted in the leftmost figure in figure 2.11. For convenience, the objective function in (2.16) might be rewritten on the penalized-loss function form, that is

$$J(x, y) = L_\epsilon(y - f(\mathbf{x})) + \lambda \|\beta\|_{\ell_2}^2$$

where $\|\beta\|_{\ell_2}^2$ is the regularizer and $\lambda = 2/C$ is the regularization constant. Note that this is the same penalty term as the one associated with ridge regression from section 2.1.1. Compared to the ridge regression, and to the OLS for that sake, SVR seeks the smallest coefficient vector that minimizes a different type of loss. Only errors greater that ϵ is contributing to the ϵ-insensitive loss function, as illustrated in figure 2.11. Moreover, relative to the RSS, large errors has limited effect since they enter the loss function in absolute rather than squared terms.

The Lagrangian associated with (2.15) is given as,

$$\begin{aligned}\mathcal{L} = \tfrac{1}{2}\sum_{j=1}^{n}\beta_j^2 + C\sum_{i=1}^{T}(\xi_t - \xi_t^*) \\ - \sum_{i=t}^{T}(\eta_t\xi_t + \eta_t^*\xi_t^*) \\ - \sum_{i=t}^{T}\alpha_t[\epsilon + \xi_t - (y_t - \mathbf{x}_t^\top\beta - \beta_0)] \\ - \sum_{i=t}^{T}\alpha_t^*[\epsilon + \xi_t^* + (y_t - \mathbf{x}_t^\top\beta - \beta_0)]\end{aligned} \tag{2.17}$$

In most cases, however, the minimization problem in is solved most easily in it *dual form* (Smola & Sc Olkopf, 2004, p. 200). The dual problem is obtained by defining a set of dual variables $\alpha_t, \alpha_t^*, \eta_t, \eta_t^*$ as the non-zero Langrangian-multipliers in (2.17). Substituting the associated first order conditions back into the Lagrangian , the minimization problem might be expressed as[23]

$$\begin{aligned}&\underset{\alpha,\alpha^*}{\text{minimize}} \;\; \tfrac{1}{2}\sum_{t=1}^{T}(\alpha_t - \alpha_t^*)\sum_{s=1}^{T}(\alpha_s - \alpha_s^*)\mathbf{x}_s^\top\mathbf{x}_t - \epsilon\sum_{t=t}^{T}(\alpha_t + \alpha_t^*) + \sum_{t=t}^{T}y_t(\alpha_t - \alpha_t^*) \\ &\text{subject to} \;\; \sum_{t=1}^{T}(\alpha_t - \alpha_t^*) = 0,\; \alpha_t\alpha_t^* = 0,\; \alpha_t, \alpha_t^* \in [0, C]\end{aligned} \tag{2.18}$$

This dual problem is a simpler convex quadratic programming problem compared to minimizing the Lagrangian in (2.17). This is useful in estimating the prediction model $\hat{f}$, since one only need to estimate α_t α_t^*, which can be obtained from the dual problem. Formally, it follows from the first order conditions of the Lagrangian with respect to β_j that

$$\hat{\beta}_j = \sum_{t=1}^{T}(\hat{\alpha}_t - \hat{\alpha}_t^*)\,x_{jt}, \quad j = 1, ..., n,$$

[23] Note that the second pair of dual variables, (η_t, η_t^*) is eliminated in the dual problem. See e.g. Smola and Sc Olkopf (2004) for the detailed approach.

The predicted outcome given a new observation $\mathbf{x}'$ is thus obtained as

$$\begin{aligned}\hat{f}(\mathbf{x}') &= \hat{\beta}_0 + \sum_{j=1}^{n}\sum_{t=1}^{T}(\hat{\alpha}_t - \hat{\alpha}_t^*)x_{jt}x_j' \\ &= \hat{\beta}_0 + \sum_{t=1}^{T}(\hat{\alpha}_t - \hat{\alpha}_t^*)\,\mathbf{x}_t^\top \mathbf{x}',\end{aligned} \tag{2.19}$$

At first sight, this mean to estimate as many parameters $(\hat{\alpha}_t - \hat{\alpha}_t^*)$ as there is observations. However, it follows from the Kuhn-Tucker conditions associated with in (2.17) that $(\hat{\alpha}_t - \hat{\alpha}_t^*)$ is only non-zero for those observations where $|y_t - f(\mathbf{x}_t)| > \epsilon$. Moreover, from (2.19) it is obvious that the observations for which $(\hat{\alpha}_t - \hat{\alpha}_t^*)$ is zero has no impact on the prediction function. Consequently, the only observations in the estimation sample needed for making new predictions are those $\mathbf{x}_t$ for which $(\hat{\alpha}_t - \hat{\alpha}_t^*)$ is non-zero. Since the regression line is determined from these observations alone, these are called *support vectors*, as they *support* the regression line (Kuhn & Johnson, 2013). The support vectors are illustrated in the rightmost panel of figure 2.11. The complexity of the prediction function is thus depending on the number of support vectors, which again depend on the cost associated with deviations larger than ϵ, controlled by the cost parameter C (equivalently $\lambda = 2/C$).

An estimate of the constant term β_0 might be computed as the average intercept of the T' observations with errors equal to $\pm\epsilon$, as

$$\hat{\beta}_0 = \frac{1}{T'}\sum_{s\in T'} y_s - \mathbf{x}_s^\top \hat{\beta} - (\pm\epsilon) \tag{2.20}$$

since for these observations the unique error is known.[24]

The fact that $\hat{f}$ only depend on the dual parameters and the cross-product $\mathbf{x}_t^\top \mathbf{x}$ is particulary useful when f is non-linear, as this allows for the use of kernel functions to generalize the regression model and encompassing non-linear functions: When it in a transformed *feature space* $\mathcal{F}$ exist a linear relationship between y and $\mathbf{x}$, such that for some non-linear mapping $\phi : \mathbb{X} \to \mathcal{F}$ applied to the set of predictors,

$$f(\mathbf{x}) = \beta_0 + \phi(\mathbf{x})^\top \beta, \quad \beta \in \mathcal{F}$$

This model might be estimated either with linear regression, as the model is still linear

[24] These observations are those for which α_t, α_t^* are between 0 and C. There are however several ways to obtain this estimate, as discussed in Smola and Sc Olkopf (2004)

in the parameters β, or with the SVR-algorithm described above.[25] In direct analog to (2.19), the solution to the SVR problem is given by

$$\hat{\beta} = \sum_{t=1}^{T} (\hat{\alpha}_t - \hat{\alpha}_t^*) \, \phi(\mathbf{x}_t)$$

and the prediction for some new observation $\mathbf{x}'$ as

$$\hat{f}(\mathbf{x}') = \hat{\beta}_0 + \sum_{t=1}^{T} (\hat{\alpha}_t - \hat{\alpha}_t^*) \, \phi(\mathbf{x}_t)^\top \phi(\mathbf{x}') \tag{2.21}$$

This approach can, however, easily become computational burdensome, in particular if $\mathcal{F}$ is a high-dimentional. Yet, in order to compute the prediction in 2.21 there is no need to evaluate $\phi(\mathbf{x})$. It is sufficient to know the inner products $\phi(\mathbf{x}_t)^\top \phi(\mathbf{x}') \in \mathbb{R}, t = 1, ..., T$. As an illustrataion, take the example provided in Smola and Sc Olkopf (2004, pp. 201–202), where $\mathbf{x} = (x_1, x_2)$ and $\phi(\mathbf{x}) = (x_1^2, \sqrt{2} x_1 x_2, x_2^2) \in \mathcal{F} = \mathbb{R}^3$, such that

$$f(\mathbf{x}) = \beta_0 + \beta_1 x_1^2 + \beta_2 x_1 x_2 + \beta_3 x_2^2$$

Then, in order estimate $\hat{f}(\mathbf{x}')$ one need to compute

$$\begin{aligned} \phi(\mathbf{x}_t)^\top \phi(\mathbf{x}') &= x_{1t}^2 x_1'^2 + 2 x_{1t} x_2 x_1' x_2' + x_{2t}^2 x_2'^2 \\ &= (x_{1t} x_1' + x_{2t} x_2')^2 \\ &= (\mathbf{x}_t^\top \mathbf{x}')^2, \qquad t = 1, 2, ..., T \end{aligned} \tag{2.22}$$

For this computation, one can use a multivariate *kernel function*. That is, instead of using the mapping $\phi : \mathbb{X} \to \mathcal{F}$ to represent each object $\mathbf{x}, \mathbf{x}' \in \mathbb{X}$ by $\phi(\mathbf{x}), \phi(\mathbf{x}') \in \mathcal{F}$, one could use the kernel function $K : \mathbb{X} \times \mathbb{X} \to \mathbb{R}$ (Vert, Tsuda, & Schölkopf, 2004),[26]

$$K(\mathbf{x}, \mathbf{x}') = \phi(\mathbf{x})^\top \phi(\mathbf{x}')$$

[25] That is, linear regression in a high dimensional space $\mathcal{F}$ correspond to non-linear regression in the low dimensional space $\mathbb{X} \subseteq \mathbb{R}^n$ (Harvey et al., 1997). See also the connection to neural networks, where the non-linear mapping ϕ corresponds to the values of the hidden nodes. In both cases these transformations might be interpreted as basis functions of the predictors.

[26] Note that these kernels differ from the ones used to compute weights for the k nearest neighbours in section 2.1.3. The function $K(\mathbf{x}, \mathbf{x}')$ should be symmetric, positive and (semi-) definite James et al., 2013. See e.g. Smola and Sc Olkopf (2004), Vert et al. (2004) for formal definitions of such kernel functions, where the last also provide alternatives to the interpretation of kernels as cross-products.

So, the prediction model can more generally be written as

$$\hat{f}(\mathbf{x}') = \hat{\beta}_0 + \sum_{t=1}^{T}(\hat{\alpha}_t - \hat{\alpha}_t^*)\, K(\mathbf{x}_t, \mathbf{x}')$$

The *linear kernel*,

$$K(\mathbf{x}, \mathbf{x}') = \mathbf{x}^\top \mathbf{x}'$$

encompasses the linear model in (2.19). This kernel, and the kernel illustrated in (2.22), are both special cases of the *polynominal kernel* of degree d (Vert et al., 2004),

$$K(\mathbf{x}, \mathbf{x}') = (\sigma \cdot \mathbf{x}^\top \mathbf{x}' + c)^d, \quad d \geq 0$$

where σ is a scaling parameter and $c > 0$ allows cross-products of order 1 to d. More complex non-linear functions might be encompassed using different kernels. A general propose kernel popular in support vector machines is the Gaussian radial basis function (RBF), (James et al., 2013; Karatzoglou, Smola, Hornik, & Zeileis, 2004)

$$K(\mathbf{x}, \mathbf{x}') = \exp\bigg(- \frac{\|\mathbf{x} - \mathbf{x}'\|_{\ell_2}^2}{2\sigma^2} \bigg)$$

where $\|\mathbf{x} - \mathbf{x}'\|_{\ell_2}^2$ again refer to the Euclidian distance between $\mathbf{x}, \mathbf{x}'$ and σ is a scaling parameter. The exact form of the transformation ϕ that correspond to this kernel is, however, not obvious (Vert et al., 2004). This illustrates that not only is there no need to evaluate this transformation in order to estimate $\hat{f}$, there is in fact no need to specify it at all (James et al., 2013). A modified version of the Gaussian RBF kernel, known to perform well in multidimensional regression problems, is the ANOVA radial basis function (Karatzoglou et al., 2004)

$$K(\mathbf{x}, \mathbf{x}') = \bigg(\sum_{j=1}^{n} \exp(-\sigma \big(x_j - x_j')^2\big) \bigg)^d$$

where σ again is a scaling parameter, and d the degree of the kernel.

The implicit mapping via kernels is often called the *kernel trick*. It is not, however, an unique property of support vector machines. For example, Hastie et al. (2009, section 12.3.7) shows that this trick can be applied as well in penalized regression problem. Both ϵ and the cost parameter C, as well as the scaling-parameters of the kernels, might be chosen by some form of empirical tuning, outlined in the introduction to this section. Details on the model specifications and estimation procedure implemented in this exercise are presented in section 3.

2.2 Benchmark models

2.2.1 (Linear) Auto-regressive models

In auto-regressive AR models the endogenous variables y_t is modeled as functions of their previous realizations. In the univariate case, with only one endogenous variable, the simplest AR model is the linear model of degree 1,

$$f(\mathbf{x}_t) = \phi_0 + \phi_1 y_{t-1}$$

In general, the AR(p) model of degree p is given as

$$f(\mathbf{x}_t) = \phi_0 + \sum_{j=1}^{p} \phi_j y_{t-j}$$

Which lags to include might be decided using an information criteria, as outlined in the illustration providen in the introduction to section 2.1. The parameter of these auto-regressive models might be estimated by OLS. In the case with more than one endogenous variable, these might be modelled as a system of auto-regressive equations,

$$\mathbf{y}_t = \Phi_0 + \sum_{j=1}^{p} \Phi_j \mathbf{y}_{t-j} + \epsilon_t$$

where $\mathbf{y}_t = (y_{1t}, y_{2t}, ..., y_{qt})^\top$ when q is the numer of dependent variables. When there are no restrictions on the coefficients in Φ_j, all equations of the system contains the same right-hand side variables. Estimating the system of equations is then equivalent to estimate each equation one-by-one. The ith dependent variable is then modelled as

$$f_i(\mathbf{x}_t) = \phi_{i0} + \sum_{j=1}^{q} \sum_{s=1}^{p} \phi_{ij} y_{j,t-s}$$

2.2.2 Naive models

As discussed in section 2.1.2, even the most well-specified model f of the relationship between y and $\mathbf{x}$ *in-sample* might not obtain the best predictions, as this relationship might change over time. As such changes are by definition not predictable (if so, then f would not be well-specified), simpler devices robust to the most common breaks might perform as well. Here, two such *naive* but robust methods are applied. The first is the double-difference device (DDD) presented in 2.1.2, obtained by differencing the estimated AR(1) model

$$\hat{y}_{T+h} = y_{T+h-1} + \hat{\phi}_1 \Delta y_{T+h-1}$$

The second is the random walk (RW),

$$\hat{y}_{T+h} = y_{T+h-1}$$

which assumes that the *change* in y_t is on average zero. That is, where the DDD is motivated by the assumption that y_t is not constantly *accelerating*, the RW corresponds to the assumption that y_t is not constantly *growing*. In particular, there is no constant term in this model, such that shifts in y_t is incorporated in the period following such a shift, as illustrated in figure 2.4.

2.3 Combined approaches

2.3.1 Decomposed model

Many economic time-series is well approximated by linear relationships , in which case estimating this relationship with pure non-linear methods as neural networks and SVR with non-linear kernels is likely to be ineffective (Teräsvirta, 2006). Anyway, there might be the case that some non-linearities is present, suggesting to decompose the relationship between y and $\mathbf{x}$ in a linear and a non-linear part,

$$y = \mathbf{x}^\top \beta + g(\mathbf{x}) + \epsilon$$

The linear unit and the non-linear unit can be estimated by different methods. Here, the linear unit is simply the AR(p) model above. The remaining, $y - \mathbf{x}^\top \hat{\beta}$ might be estimated using a method that allow for non-linearities, such as the neural networks and SVR approaches outlined above. Forecasts is then obtained for each part separately, and the sum of them constitute the actual forecast $\hat{y}_{t+h}$, see further details on the implementation section 3. [27]

2.3.2 Combining point forecasts

Absent any perfect forecasting method outperforming every other, forecast combination allows for diversification gains (Timmermann, 2006). One may hope that all predictions alone deviates from the actual value in different directions, such that, when combined, they are closer to the true value. Obviously, this technique work best when the predictions error are not correlated, in direct analogue to the intuition behind random forest.[28]

There are many ways to construct averages of forecast. Diebold and Shin (2017), for example, uses penalized regression to obtain weights for different forecasts. Aastveit,

[27] Goel, Melnyk, and Banerjee (2017) do a similar exercise, combining a VAR(p) and recurrent neural networks. In contrast to the approach outlined above, they forecasts the *forecasting errors*, rather than the residuals, from the linear specification.

[28] Random forest, and any other estimator based on bagging, constitute them selves an ensemble of prediction models.

Gerdrup, and Jore (2011) compute weights based on (the inverse) MSE when forecasting the Norwegian inflation using Norges Banks' system for averaging models SAM, and a measure based on the log of the predicted densities when forecasting gross domestic product (GDP). Here, only simple unweighed averages are evaluated, described in detail in the next section.

3 Forecasting strategy

The methods presented in the previous section is used to obtain short-term forecasts for the Norwegian GDP-growth and inflation rate. A direct approach is applied, where the dependent variable h steps ahead, y_{t+h}, is modeled as a function of the set of n predictors at time t,

$$y_{t+h} = f_h(\mathbf{x}_t) + e_{t+h}$$

where $\mathbf{x}_t = (x_{1t}, ..., x_{nt})^\top \in \mathbb{X} \subseteq \mathbb{R}^n$ and e_{t+h} is the forecasting error for horizon h. The h-step ahead point forecast at the end-of sample observation T is obtained as $\hat{y}_{T+h} = \hat{f}_h(\mathbf{x}_T)$. Applying a direct forecast approach is thus to estimate a single model for each horizon, but avoid the necessity to estimate the evolution of $\mathbf{x}_t$ (Garcia et al., 2017). Each method is applied both to the univariate case, where $\mathbf{x}_t$ include only lags of the dependent variable, and to the case where in addition measures of other economic time series are included. The next sections present the data and motivate the choices made in the implementation of the empirical exercise, related to the timing of the forecast made and how these are obtained in the real-time setting, as well as to the estimation and comparison of the different models.

3.1 Data

3.1.1 Actuals

The repeated revision of the QNA figures give rise to the issue of choosing which measure to use as *actuals* for the Norwegian GDP, ie which measure of GDP to use in evaluating forecast accuracy. The the first release is published in the QNA by Statistics Norway (SSB) 40-50 days after the end of the reference quarter, together with revised figures for the past four quarters. In August/September each year, the publication include revised figures for the two previous years. At this point, the results for all quarters in the second to last year is considered final. That is, the final GDP release is 21 months after the end of the year of the reference quarter (23 months until August 2016). Due to structural revisions undertaken affecting all previous observations, the last available data might not coincidence with the these final figures.[29] These revisions might represent definitional or methodological changes, such that comparing a forecast $\hat{y}_{T+h}$ made conditional on data available *before* these changes took place with the measure of y_{T+h} incorporating these changes might be unfair. Hence, arguing that the 'first final' releases represent the most 'true' measures, these are used as actuals in forecasting GDP growth. To be precise, the figures from the November publication of QNA in the second year after the reference quarter are used as actuals, which was considered the final release until 2016.

[29]See the detailed publication cycle for the Norwegian QNA figures and an overview of main revisions at https://www.ssb.no/en/nasjonalregnskap-og-konjunkturer/statistikker/knr.

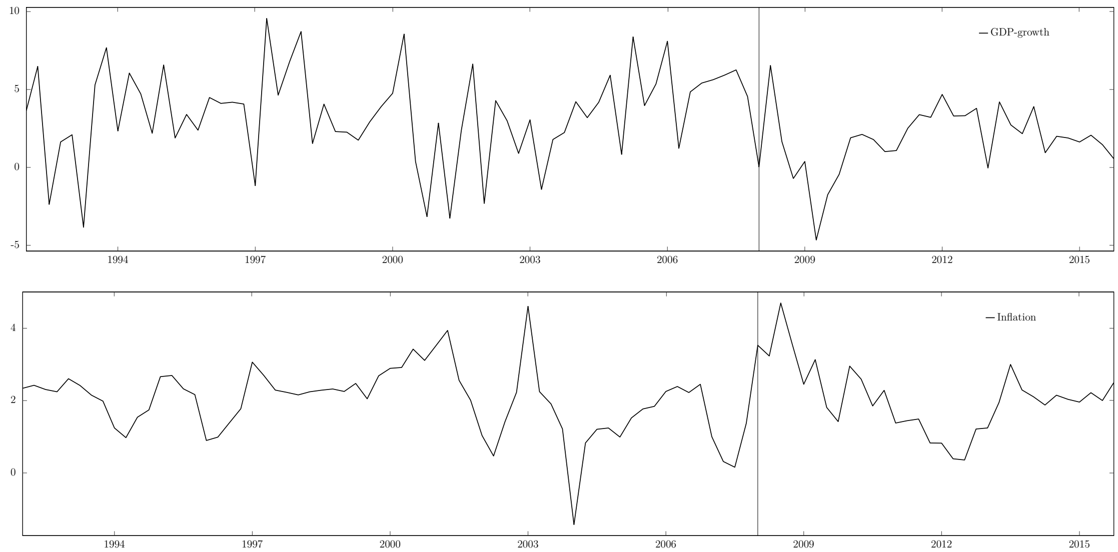

Figure 3.1: Actuals. *Top:* Four quarter change in GDP. *Bottom:* Four quarter change in the quarterly average of the CPI. The vertical line denote the first forecasting origin, 2008Q1.

The inflation rate, on the other hand, is not subject to revision. There is, however, several price indexes including different groups of commodities on which to base this measure. The choice of the unadjusted inflation rate was made simply because this measure has the longest history, in order to provide enough observations due to the quarterly frequency of the forecasts made. Moreover, the four quarter change in the *quarterly average* of the monthly consumer price index (CPI)-index is used as actual, not the annual change in this index. This measure will be referred to as inflation.

3.1.2 Variable selection

The *ex ante* variabel selection, the choice of which variables to include as conditional variables or predictors in the multivariate forecast exercise, is based on availability, previous literature and economic reasoning. The same set of conditioning variables is used for forecasting both GDP-growth and the inflation rate, which include a set of timely indicators and macroeconomic series for the Norwegian economy, as well as foreign interest rates and inflation. Additionally, in order to implement the analysis in real-time, an important factor in the choice of predictors has been the possibility to obtain vintages for revised series.[30] The upper panel in table 3.1 list all variables in the data set. The contemporaneous observations as well as the first lag is included as conditioning variables. In addition, univariate auto-regressive relationships for each of two the dependent variables

[30]Through Norges Bank I have been lucky to access such data, yet, building a real-time data base is very time consuming, therefore revised series has been avoided. Data from OECDs real-time database is also used. Here, all vintages can be read directly into **R** through the `OECD`-package, but only a limited number of series is provided.

are subject to estimation, where the eight first lags constitute the set of conditioning variables. The sample span from 1990Q1–2015Q4. Due to differences and lag creating, the effective sample include observations from 1991Q4–2015Q4.

3.1.3 Temporal aggregation

All forecasts are made at the quarterly frequency, the frequency of the Norwegian GDP release. There are, however, both monthly and quarterly series among the conditioning variables, and the monthly series are thus aggregated to the lower frequency. This is done either by taking the average of the monthly series (stock variables)[31] or by summing over these (flow variables). When the last monthly figures in a quarter is *not* published before a forecast is computed, only the first or first pair of observations are used in this conversion to the quarterly frequency – as a temporary measure or an estimate of the final aggregate For the quarterly series, the observation from the previous quarter is used, see also section 3.2.1 which describe the timing of the forecasts. The resulting quarterly series are then expressed in terms of their four quarter relative change, with the exception of rates and a couple of constructed indexes. The lower panel in table 3.1 lists the data, along with the publication delay, and the temporal aggregation as well as transformations undertaken to remove stochastic trends. The sample correlation between the conditioning variables and the actuals for each horizon is plotted in figure 3.2.

3.2 Forecasting in real-time

In real-time, there is continuous flow of information from which we can try to say something about the future. When using this information to make predictions of future economic variables, the data base on which these predictions are conditioned on is changing. These changes might reflect for example new data releases or revised figures of previous releases. This highlight a trade-off between *timeliness and accuracy* (J. Mitchell, 2009); the earlier a forecast is made, the less (timely is the) information is taken into account. When replicating real-time forecasting, only data available to a forecaster at the particular point in time in the past should be used, both in estimating the models and in computing the actual forecasts. The next sections will first present the timing of the forecasts applied, before explaining how model estimation is undertaken facing this changing database.

3.2.1 Timing of the forecasts

Economic figures are often first available some time after the reference period. Formally, of the n series included as conditioning variables in $\mathbf{x}_T$ only j are known at the time of an end-of sample observation T. Each of the $n-j$ remaining series are available with a

[31]If the monthly series is it self an average, the quarterly average is taken of these monthly averages, abstracting from the fact that months have different number of days.

Table 3.1: Data description and variable transformations

Variabel name	Variabel description
al05110.1	Unemployed. Both sexes. 15-74 years. Persons (per cent).
bb03723	Dwellings started.
bfSP500	SP500. Inflation adjusted. Monthly average closing prices..
bfMEI-FIN	Long term interest rates. Germany/Euro-area. Percent p.a.
bfMEI-FIN.1	Short term interest rates. Germany/Euro-area. Percent p.a.
bfMEI-FIN.2	Long term interest rates. Norway. Percent p.a.
bfMEI-FIN.3	Short term interest rates. Norway. Percent p.a.
bfbrentblend	Europe Brent Blend. Spot price. Monthly. FOB.
bfEXR.M.I44	Exchange rate. Import-weighted.
bfFNI	Financial news index (FNI). Median. Monthly average.
ppMEIA-M3	Broad money. National currency.
ei07095	Index of industrial production. Calender adjusted. 1995 = 100.
ei08267	Business tendency survey. Manufact., mining and quarrying. Confidence indiator.
inMEIA-CLI	Composite leading indicator: amplitude adjusted. Index.
nk09190	Gross domestic product Mainland Norway. Market values. Constant prices.
os07391	Distributed taxes, total.
ppMEI-PRICES	Consumer prices - all items. OECD Eur. Annual change. Percentage.
pp03013	All-item index. Consumer Price Index (2015=100).
pp07097	Producer price index. Domestic and export market, total. 2000 = 100.
suMEI-BTS-COS	Business tendency surveys. OECD Europe. Manufacturing. Condfidence indicator.
suMEI-BTS-COS.1	Consumer opinion surveys. OECD Europe. Manufacturing. Condfidence indicator.
utMEIA-IMPORT	International trade in goods - imports. National currency.
utMEIA-EXPORT	International trade in goods - exports. National currency.
vt07129	Retail sale, ex. motor vehicles and fuel. Volume index. Working days adj. 2000 = 100.

Variabel name	Fr.	Source	Table/database	Pub. d.*	First vint.	T. agg.	Transf.
al05110.1	Q	SSB	05110	35	-	-	ddiff
bb03723	M	SSB	03723/10996	5	-	sum	growth
bfSP500	M	MULTPL	SP500	0	-	ave	ddiff
bfMEI-FIN	M	OECD	MEI-FIN	10	-	ave	diff
bfMEI-FIN.1	M	OECD	MEI-FIN	10	-	ave	diff
bfMEI-FIN.2	M	OECD	MEI-FIN	10	-	ave	diff
bfMEI-FIN.3	M	OECD	MEI-FIN	10	-	ave	diff
bfbrentblend	M	EIA	brentblend	0	-	ave	growth
bfEXR.M.I44	M	NB	EXR-M.I44	0	-	ave	ddiff
bfFNI	M	Retriever/CAMP(BI)	FNI	7	-	ave	diff
ppMEIA-M3	M	OECD	MEI-ARCHIVE	45	1999M2	sum	growth
ei07095	M	SSB	07095/03555	35	-	ave	ddiff
ei08267	Q	SSB	08267	28	-	-	-
inMEIA-CLI	M	OECD	MEI-ARCHIVE	45	2001M1	ave	growth
nk09190	Q	SSB/NB	09190	40-50**	2004Q1	-	growth
os07391	M	SSB	07391/05284	15	-	sum	growth
ppMEI-PRICES	M	OECD	MEI-PRICES	10	-	ave	diff
pp03013	M	SSB	03013	10	-	ave	growth
pp07097	M	SSB	07097/03692	15	-	ave	growth
suMEI-BTS-COS	M	OECD	MEI-BTS-COS	10	-	ave	diff
suMEI-BTS-COS.1	M	OECD	MEI-BTS-COS	10	-	ave	diff
utMEIA-IMPORT	M	OECD	MEI-ARCHIVE	45	1999M2	sum	growth
utMEIA-EXPORT	M	OECD	MEI-ARCHIVE	45	1999M2	sum	growth
vt07129	M	SSB	07129/03820	15	-	ave	growth

Note: *Publication delay in days after end of reference quarter as of January 2018. Where not excact delay was stated, an (approximate) average is reported.**Publication delay of first release, see section 3.1.1. "-" translates to *not relevant*. *ave* is short for average, *diff* for difference, *ddiff* for double-difference.

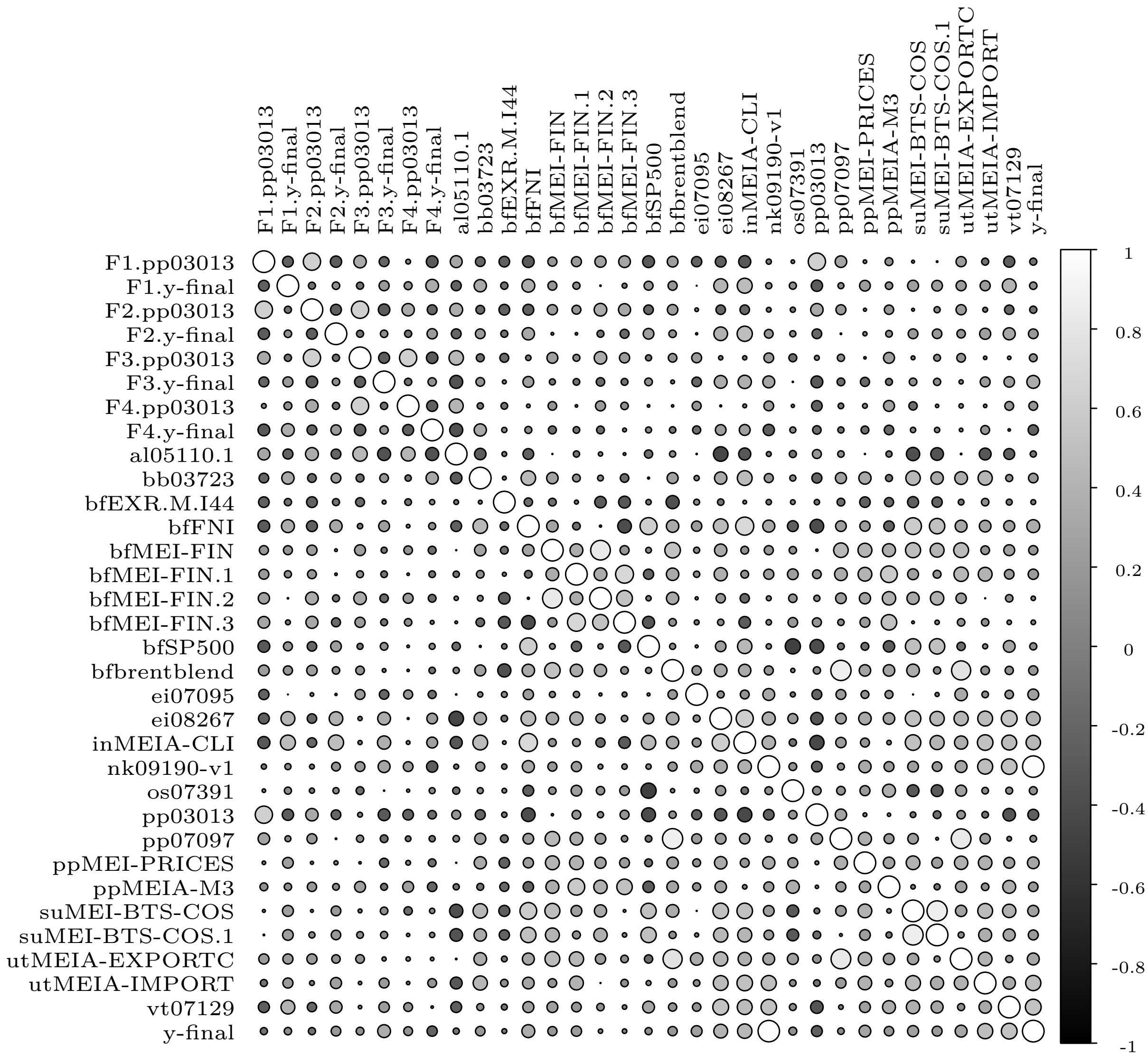

Figure 3.2: Variable correlation matrix. 'F' refer to forward lag, 'L' to backward. Based on full quarterly figures. See variable descriptions in table 3.1

delay. Hence, the information set on which forecasts are conditioned depend on what time the variables included are measured; a h-steps ahead forecast made conditional at information available at time T may differ from that made conditional on information known at time $T + \delta$. In particular, when $h = \delta = 0$ a *nowcast* is computed, whereas $h < \delta$ result in a *backcast* – which is relevant only when the variable of interest y_{T+h} is still unknown at time $T + \delta$.

Whereas the forecasts could be updated every time new information is received, a simpler schedule is followed: For the $h = 0$ horizon, there is made one nowcast of the inflation rate and two nowcasts/backcasts for the GDP-growth. The first is computed at the end of the last month in the reference quarter, at $T + 0$. This nowcast is made conditional on the predictors assumed published without delay, but with incomplete information of the remaining. The second nowcast is made one month after the end of the reference quarter, at time $T + 1/3$. At this point most of the monthly series are available and included in the information set. At time $T + 2/3$, all information from quarter T is known, in particular the first release of SSB's GDP release. At this point, the forecast horizon is extended and forecasts for the next quarter $T + 1$ and up to four quarters ahead are computed.[32] In total, that constitute six forecasts for the horizons for $h = 0, 1, 2, 3, 4$ for the GDP-growth, five for the inflation rate. In the univariate case, only the four latter horizons are considered as only the release of the GDP and CPI figures are relevant for these forecasts.

A real-time example follows, for convenience: The first forecast origin is 2008Q1. At the end of the quarter, the first nowcast is made for both inflation and GDP, based on the first release of GDP growth and the inflation rate for the previous quarter as well the most timely information (assumed to be available without delay) from 2008Q1. After one month, in the end of April 2008, a backcast of the 2008Q1 GDP-growth is made (not for the inflation rate, which at this point already is known). At the end of the second month, in May 2008, after SSB has published the first QNA release for 2008Q1, forecasts for the following four quarters are produced. This procedure is repeated until the last forecasts are made for 2015Q4. That makes $32 - h$ forecast for horizon h.

3.2.2 Estimating forecasting models in real-time

Wheras the above presented the timing of the computation of the forecasts, these forecasts are obtained with an estimate $\hat{f}_h$ which needs also need to take into account the changing

[32]The real-time database constructed is based on publication delays as reported from the different sources in January 2018. Following a simpler schedule, computing forecast only at a monthly frequency this is assumed to be an good approximation of the past information flow. Note also that both the $T+0$ and $T+1$ are strictly said nowcasts, as the forecast $\hat{y}_{T+1}$ is computed at time $T+2/3$, ie inside the subsequent quarter $T + 1$. They differ, however, in that the first takes into account contemporaneous information, the second does not.

database. In particular, when data is subject to revision, one needs to decide which *vintage* of data to use in estimation of the model. Here, adapting the notation from above, the $T+\delta$ vintage refers to the data as it is measured at time $T+\delta$, which might differ from the subsequent $T+\delta'$ vintage if some series are subject to revision (or, of course, if new releases are included). The real-time dataset used in this exercise is constructed in such a way that, when a forecast is going to be made conditional on the information most up to date at time $T+\delta$, each observation t in the estimation sample contains the most up-to date information at time $t+\delta$. This means that each row of the estimation sample belongs to the same vintage, but that all rows corresponds to different vintages.[33] The relationship estimated is thus

$$y_{t+h|t+\delta} = f_h(\mathbf{x}_{t|t+\delta}) + \epsilon_{t+h|t+\delta}, \quad t = 1, 2, ..., T-h$$

Intuitively, since the actual forecast will be made conditional on the information most up to date at time $T+\delta$, it makes sense to also estimate the relationship between series most up to date at time $t+\delta$, rather than between revised figures for $t < T$. The latter would be the case if one used all information most up to date at time $T+\delta$ in estimation. Whereas this approach might be more close to *real* real-time forecasting, Koenig, Dolmas, and Piger (2003) shows that one would estimate spurious relationships if the revision process of the left-hand side and right-hand side variables are correlated.[34]

Now, in the case of forecasting GDP growth, the left-hand side variable is subject to a substantial publication delay Δ, no less than 21 months (for the Q4 figures). If one should base the forecast of the final GDP-relase y_{T+h} on an *direct* estimate of the relationship between this measure and the conditioning variables at the time, one would need to estimate

$$y_{t+h|t+\delta} = f_h(\mathbf{x}_{t|t+\delta}) + \epsilon_{t+h}, \quad t = 1, 2, ..., T-\Delta-h,$$

since at time $T+\delta$ the last known h steps ahead observation is $T-\Delta-h$. This will obviously be suboptimal if $\hat{f}_h$ is no longer a good approximation of the relationship between y_{t+h} and $\mathbf{x}_t$ at time $t=T$. Instead, the first release of GDP-growth is used as left-hand side variable. Assuming that these are efficient predictions of the final release,

[33] Each variable in a real-time data base is presented as an matrix, not only a vector, with rows corresponding to observations and columns the different vintages. The approach outlined corresponds to use the diagonals of this matrix, where the first release of the variable is to find on the main diagonal, the rth release of at the rth off diagonal.

[34] Note that when data is *not* revised, there will be no difference. Koenig et al. (2003) denotes this *real-time vintages* as opposed to *end-of-sample vintages*, see also the contributions to this discussion given in Clements and Galvão (2008), Stark and Croushore (2002).

meaning that the succeeding revisions is not predictable at the time of the first release, Koenig et al. (2003) argue that using later, revised releases will decrease accuracy of the estimated relationship as the additional information these incorporate can not be predicted at the time of the forecast origin.[35] The exception is for the now- and backcast. Since the most up-to date information at time $T+0$ and $T+1/3$ is going to be used to estimate $\tilde{y}_{T|T+2/3}$, which again is an estimate of the 'first final' release $y_{T|T+\Delta}$, the following relationship is estimated

$$\tilde{y}_{t|t+2/3} = f_h(\mathbf{x}_{t|t+\delta}) + u_{t|t+2/3}, \quad t = 1, ..., T-1,\ \delta = 0, 1/3$$

That is, the left-hand side belong to a later vintage than the right hand side. To illustrate, the linear model containing p lags of $\tilde{y}_t$ and $n-p$ additional conditioning variables, would be estimated as,

$$\tilde{y}_{t+h|t+2/3} = \phi_0 + \sum_{j=1}^{p} \phi_j \tilde{y}_{t-j|t+2/3} + \sum_{k=1}^{n-p} \beta_k x_{t|t+2/3} + \epsilon_{t|t+2/3} \quad t = 1, 2, ..., T-h$$
$$\tilde{y}_{t|t+1} = \phi_0 + \sum_{j=1}^{p} \phi_j \tilde{y}_{t-j|t+\delta} + \sum_{k=1}^{n-p} \beta_k x_{t|t+\delta} + \epsilon_{t|t+\delta}, \quad t = 1, 2, ..., T-1$$

for $h > 0$ and $h = 0$, respectively. Again $\tilde{y}$ illustrates that the first release of GDP is used in estimation. In the case of inflation, which is not revised, $\tilde{y}$ equals y.

Two simplifications are made. First, since the vintages from the beginning of the estimation sample is not available, the first available vintage is used for all proceeding observations of the revised series (the first vintages available is listed table 3.1). In particular, the first vintage for the GDP-growth is from 2004Q1. This vintage does in addition define the 'first final' release for observations up to 2001Q4, since the actual first figures are not available. Second, whereas all differences and growth rates computed as a part of variable construction is within each vintage, the double difference device is computed across vintages. That is, using $\Delta \mathbf{x}_t = \mathbf{x}_{t|t+\delta} - \mathbf{x}_{t-1|t+\delta-1}$. If $\mathbf{x}_{t-1}$ is revised between $t+\delta-1$ and $t+\delta$, then $\Delta \mathbf{x}_t$ will reflect both the change in $\mathbf{x}_t$ from the previous

[35] Hence, the resulting forecasts are forecast of the first-release, not the final release per se. Annex A.1 include a plot comparing these two releases. The crucial factor of this choice was that the dependent variable in this case is a vector with the first release of GDP-growth, not a matrix with vintages for each forecast origin, which eases the data organization. Other real-time short-term forecasting exercises applied to Norwegian data use both strategies, e.g. Thorsrud (2017) use the first release as dependent variable in nowcasting Norwegian GDP-growth, whereas Aastveit et al. (2011) uses the latest available data vintage at each end-of-sample observation in forecasting GDP and inflation. The formed does, admittedly, perform a briding from the first-release forecasts to later releases considering that the first release may *not* be effective. This is excluded here, as comparing the different methods rather necessarily than obtain the best possible forecast of GDP-growth is central.

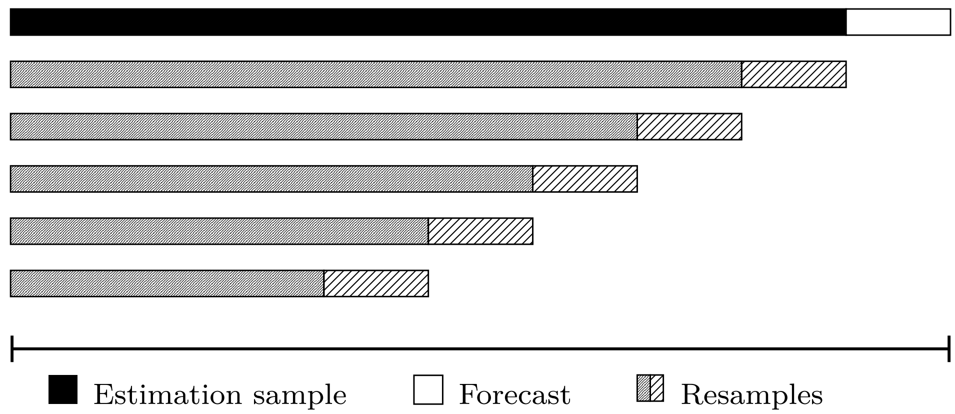

Figure 3.3: Recursive scheme for parameter tuning and forecasts computation. For each set of tuning parameters, the model is estimated on subsamples of the estimation sample (dark pattern) and used to predict the $T^r + h$th observation of the rth resample (light pattern). The parameters that shows best performance across all subsamples is then used to re-fit the model on the entire estimation sample (black), before the forecast $\hat{y}_{T+h|T}$ is made (white).

period *and* the revision process. Hence, the difference device estimates might be more noisy than what optimally would be the case.

3.3 Model estimation

3.3.1 Parameter tuning

Most of the considered models require the determination of a set of parameters regulating model complexity as a part of model estimation, which has been refeered to as tuning parameteters or regularization parameters – that is, the models need to be 'calibrated'. As noted in the introduction to section 2.1, these parameters might be determined by first defining a set of candidate values for these parameters, estimating the model with each set of parameters, before deciding on a final model with tuning parameters that gave the best performance of the model according to a given criteria. Here, an *emprical tuning* strategy is applied, where the estimation sample repeatedly is splitted into training and validation sets, the models estimated on the former for each candidate set of tuning parameters and the expected prediction error (MSE) is directly estimated by predicting the hold-out observations. The parameters that gave the lowest MSE are then used to re-fit the model on the complete estimation sample, before computing the final forecast. Because future data might contain information about past data, due to the dependence on time, fitting a model on future data before measuring how well it predict past data might lead to overly favourable estimates of the model's performance. Hence, the sample splits involved in tuning are such that the in-sample held-out observations always are those following the observations on which the model is fitted. The in-sample experiment for parameter tuning and the computation of the actual forecasts thus follows the recursive scheme, which is illustrated in figure 3.3, on an expanding estimation sample. The repeated estimation required for tuning is time consuming, and the number of resamples is thereofre limited to 10, such that predictions of the 10 last observations in the estimation sample is used to decide on tuning parameters. All models are re-estimated at each origin, including the selection of tuning parameters.

3.3.2 Model spesifications and choice of candidate tuning parameters

No tuning is done for the particular general-to-spesific algorithm (GETS) and the benchmark models, nevertheless these methods does as well require certain parameters to be determined as a part of model spesification, which is presented in the following, together with the choice of candidate tuning parameters for the remaining methods.[36] Table 3.2 summarizes this subsection, and provides an overview over the forecasting models and the associated specification choices.

Benchmark models

The AR(1) model include only the first lag of the dependent variable and a constant. The number of lags in the AR(p) model is chosen according to the Akaike's information criterion (AIC). In particular, with at most n lags. The vector auto-regressive model (VAR(4)) include as endogenous variables GDP-growth and inflation rate, as well as the short-term Norwegian interest rate (3 month NIBOR). Four lags of the endogenous variables are included. The double-difference device (DDD) use the estimated persistence from the AR(1)-model.

General-to-spesific models (GETS)

In selecting variables with the algorithm, a significance level of 1/n is chosen as criteria for determining variable relevance, where n is the number of predictors. When the general unrestricted model (GUM) is saturated with impulse- or stepindicators (GETS-IIS/SIS) this value is sat to a lower level of 0.01, due to the inflation in indicators included as T increases. These models are estimated with the `gets`-package in **R**, documented in Pretis et al. (2016). Because this package does not allow to jointly select over conditioning variables and indicators, the indicator saturated GUMs include the retained variables from the non-saturated specification, but only the indicators are selected over. Finally, the

[36]The forecasts is obtained over a larger time-span, where candidate tuning parameters has been adjusted according to what seems most reasonable. Hence, even though it was the intention, it might be the case that some models have been estimated with other candidate tuning parameters than those reported here. The selected tuning parameters is, however, recorded and available upon request. Annex A.4 report session-information from `R`, including the package versions used to obtain forecasts.

parameter estimates obtained in from these specifications is used to compute associated difference devices GETS-IIS/SIS-DDD.

Penalized regression models

For the penalized regression models, the possible values of the regularization parameter λ are 100 values decreasing on the log-scale between $\lambda_{\max}$ and $0.001 \cdot \lambda_{\max}$, where $\lambda_{\max}$ is characterized as the value of λ where all coefficients are equal to zero. These values are obtained with the `cv.glmnet` function of the `glmnet`-package in **R**, documented in Friedman et al. (2010). For the elastic net (ELNET), α is set to nine values between 0 and 1, simply $0.1, 0.2, ..., 0.9$. Hence, this estimator is neither exact equal to the Lasso nor the ridge, rather a weighted average of the two. Both the empirical tuning approach outlined above, and the AIC is used to select λ (the resulting models are denoted CV and AIC, respectively).

k-Nearest neighbours

Both an un-weighted and a weighted version of k-Nearest neigbours is applied. For the unweighted version, (k-NN), k might take values from 1 to 10. In the weighted version (wk-NN) k takes values equal to $1, 5, 10, 15, 20, n-1$. Weights computed with Epanechnikov's kernel and the Gaussian kernel are as well subject to tuning. The models are estimated with the `kknn`-package in **R** (Hechenbichler et al., 2004).

Random forest

The trees in the random forests (RF) are grown until there there are at most 5 observations in each node. There is grown B = 500 trees. With n predictors in total, the number of candidate split variables m is $1, n/6, n/3, 2/3n$ and n rounded up or down to the nearest integer. Here $n/3$ is the default value in the `randomForest`-package (Liaw, Wiener, & Andy Liaw, 2018) used in estimation, and Breiman and Cutler (2004) recommends to include as well the half and the double as candidate values.

Support vector regression

In the support vector regression (SVR), ϵ is held constant at 0.1 and only the cost-parameter C is obtained by tuning, as suggested by Kuhn and Johnson (2013, chapter 7.3). Four different kernel functions is applied: the linear kernel (SVR-LIN), the polynomial kernel of degree 2 (SVR-POLY), the Gaussian radial basis function (SVR-RBF) and the modified version (SVR-ANOVA) of degree $d = 1, 2$.. The candidate values for the cost-parameter are sat between $2^{-5}, 2^{-1}, ..., 2^{8}$ for the different kernels (see table 3.2), following examples given in Kuhn and Johnson (2013). For the two last kernels, there is an additional parameter σ that needs to be determined. Letting $\mathbf{x}$ being the predictors in the estimation sample, the optimal value of σ is shown to lie between the 0.1 and

0.9 quantile of $\|\mathbf{x} - \mathbf{x}_{T+h}\|_{\ell_2}$ (Karatzoglou et al., 2004). These quantiles is estimated for each particular sample, using the `sigest` function from the `kernlab`-package in **R**, as documented in Karatzoglou et al. (2004). The average of the 0.1 and 0.9 quantile is used in estimation.

Neural networks

The neural networks is the most time-consuming models to estimate, and the grid of candidate tuning parameters to search through is therefore smaller. The sigmoid function is used as the transfer function for the hidden nodes in both networks. James et al. (2013, chapter 11) recommends to fit a large network, and regularize the weights. For the basic Feed forward neural network (FFNN), only $n/3$ number of hidden nodes is therefore evaluated, arranged in one single hidden layer. The weight decay parameter λ takes values in 0.1, 0.5, 1, 2, 3. Moreover 10 networks is computed with randomly chosen initial weights, and every prediction is computed as the average from these networks. The estimation is obtained using the `avNNet`-function in the `caret`-package (Kuhn, 2017). The recursive Elman network (RNN) has possibly $n/12, n/6$ nodes, additionally $n/3$ in the univariate case, rounded down to the nearest integer. Neither weight decay nor averaging over fitted networks is performed for this model, therefore the size of the network is reduced with the intention to avoid overfitting. This network is computed using the `RSNNS`-package in **R**, documented in Bergmeir and Benítez (2012a).

Combined approaches

The model decompesed in a linear and non-linear unit combines the AR(p) model, with lags selected with the AIC and the non-linear SVR and neural-networks models. The estimation of the non-linear unit involve selecting over the same tuning parameters as reported above. In the tables, these are referred to as AR+ models. Only simple averages is constructed for the forecasting ensembles. The total average (Tot. Ave.) is obtained as the average of all predictions excluding the benchmark models. Also, averages is constructed for each group of models: the benchmark models (Ave. BM) which include the (V)AR, the RW and the DDD; the linear models (Ave. Linear), that is GETS and penalized regression; The local methods (Ave. Local), including k-NN and random forest; The non-linear models (Ave. Non-linear), the SVR and the neural network models;[37] and finally, the AR + non-linear models. There might be the case that these groups of forecasts are highly correlated, reducing the potential diversification gains from this strategy. However, this approach allows for an easy way to compare the average performance of this ordering of the models.

[37]Due organizational matters in the estimation of these averages, the linear kernel SVR model is included in this group of non-linear forecasts.

Table 3.2: List of model specifications and associated tuning parameter values.

Model	Parameter values
Benchmark models	
AR(1)	-
AR(p), info. crit.	$p \leq 8$
Random walk (RW)	-
Differenced AR(p) (DDD)	$\hat{\phi}$ from AR(1)
General-to-spesific modelling	
GETS	$\alpha = 1/n$
GETS + IIS or SIS (GETS-IIS/-SIS)	$\alpha = 0.01$
Differenced GETS (DDD-GETS/-IIS/-SIS)	$\hat{\delta}$ from respective GETS-models
Penalized regression	
Ridge (Ridge CV/AIC)	$\lambda \in S(\alpha; \mathbf{x}_t, y_t)^*$
Lasso (Lasso CV/AIC)	$\lambda \in S(\alpha; \mathbf{x}_t, y_t)^*$
Elastic net, cross-validated (ELNET-CV)	$\lambda \in S(\alpha; \mathbf{x}_t, y_t)^*$
	$\alpha = 0.1, 0.2, ..., 0.9$
Elastic net, info.-criteria (ELNET-AIC)	$\lambda \in S(\alpha; \mathbf{x}_t, y_t)^*$
	$\alpha = \alpha^{\mathrm{CV}**}$
***k*-Nearest Neighbours**	
k-Nearest neighbours (*k*-NN)	$k = 1, 2, ..., 10$
Weighted *k*-Nearest neighbours (*wk*-KNN)	$k = 1, 5, ..., 20, n-1$
	$K(d)$: Epanechnikov, Gaussian
Random forest	
Random forest (RF)	$T_{\min} = 5$
	$m = 1, n/6, n/3, 2/3 \cdot n, n$
Support vector regression	
Linear kernel (SVR-LIN)	$C = 2^{-2}, 2^{-1}, ..., 2^5$
Polynominal kernel (SVR-POLY)	$C = 2^{-4}, 2^{-1}, ..., 2^6$
	$\sigma \in \{0.001, 0.01, 0.1\}, d = 2$
Gaussian RBF kernel (SVR-RBF)	$C = 2^{-4}, 2^{-1}, ..., 2^6$
	$\sigma = \hat{\sigma}^{***}$
Anova RBF kernel (SVR-ANOVA)	$C = 2^{-2}, 2^{-1}, ..., 2^6$
	$\sigma = \hat{\sigma}^{***}$, $d = 1$
Neural networks	
One-layer feed forward neural network (FFNN)	$h = n/3$
	$\lambda \in \{.01, 1, 1.5, 2, 2.5, 3, 5\}$
Recurrent neural network (RNN)	$h = n/12, n/6, n/3$
Combined approaches	
AR(p) + non-linear (AR+)	$p \leq 8$
Ensembles (Ave. BM/Linear/Local/Non-lin./AR+/Tot. Ave)	simple averages of forecasts

Note: * A sequence of 100 values for λ decreasing from $\lambda_{\max}$ to $\lambda_{\min} = 0.001 \cdot \lambda_{\max}$ on the log-scale, whith $\lambda_{\max}$ such that the $\hat{\beta}(\lambda_{\max}) = 0$. These values are provided by the `glmnet`-package in **R** for each estimation sample, see Friedman, Hastie, and Tibshirani (2010). ** The optimal α obtained by empirical tuning. *** σ is a parameter of the Gaussian RBF kernel $K(\mathbf{x}, \mathbf{x}')$, estimated for each estimation sample with help from the `kernlab`-package in **R**, see Karatzoglou, Smola, Hornik, and Zeileis (2004), as described in the main text.

3.4 Forecast evaluation

The mean squared forecasting error is used to assess forecasting accuracy and to compare the different forecasting models. The statistical significance of the observed differences in this measure are tested with the modified DM test proposed by Harvey et al. (1997). This section provide an outline of the implementation of this test, closely related to the original DM test due to Diebold and Mariano (1995), where the modified test was shown to perform better in small samples, in particular for forecast horizons $h > 1$.

Given two forecast $\hat{y}_t^i, \hat{y}_t^j$ with associated forecasting errors e_t^i, e_t^j, the DM test compare forecast accuracy via the null hypothesis of a zero expected *loss differential*,

$$H_0: \quad E(d_t^{ij}) = E[L(e_t^i) - L(e_t^j)] = 0,$$

where L is a function reflecting how the forecast accuracy is assessed, ie $d_t^{ij} = (e_t^i)^2 - (e_t^j)^2$ when comparing quadratic losses. Under the assumtion that d_t^{ij} is covariance stationary, the test statistic is

$$DM^{ij} = \frac{\bar{d}^{ij}}{\hat{\sigma}_{\bar{d}^{ij}}} \quad \xrightarrow{D} \quad N(0,1) \tag{3.1}$$

with $\bar{d}^{ij} = N^{-1} \sum_{t=1}^{N} d_t^{ij}$, N equal to the number of forecasts compared and $\hat{\sigma}_{\bar{d}^{ij}}$ a consistent estimate of the standard error of $\bar{d}^{ij}$ (Diebold, 2015). As the sequence d_t^{ij} is likely to be serially correlated for a h-step ahead forecast, the standard error in the denominator of 3.1 should be calculated robustly. Assuming that there is no autocorrelations higher than of order $h-1$ of the sequence d_t^{ij}, the asymptomatic variance of the sequence is (Harvey et al., 1997, p. 282)[38]

$$\sigma^2_{\bar{d}^{ij}} \approx N{-}1 \left(\gamma_0 + 2 \sum_{k=1}^{h-1} \gamma_k \right) \tag{3.2}$$

where γ_k is the kth auto-covariance of d_t^{ij}. The auto-covariance may be estimated by

$$\hat{\gamma_k} = N^{-1} \sum_{t=k+1}^{N} (d_t^{ij} - \bar{d}^{ij})(d_{t-k}^{ij} - \bar{d}^{ij})$$

in order to obtain a consistent estimate $\hat{\sigma}^2_{\bar{d}^{ij}}$ and the implied test statistic DM_{ij}.

The DM test was shown to be over-sized in small samples (Diebold & Mariano, 1995),

[38] For an optimal h-step ahead forecasts, the sequence of forecast errors, and hence the loss differential, follows a moving average process of (maximum) order $h-1$. This is assumed to be a reasonable benchmark for h-step ahead forecast in estimating $\hat{\sigma}$, also when forecasts is not optimal (Diebold & Mariano, 1995; Harvey et al., 1997).

even more as the forecast horizon h increases (Harvey et al., 1997). In the modified version, Harvey et al. (1997) replaces the estimator in (3.2) with the approximately unbiased estimator of the variance,

$$\hat{\sigma}^{2*}_{\bar{d}^{ij}} = N^{-1}\left(\hat{\gamma}^*_0 + 2N{-}1\sum_{k=1}^{h-1}(N-k)\,\hat{\gamma}^*_k\right), \quad \text{where} \quad \hat{\gamma}^*_k = (N-k)^{-1}N\,\hat{\gamma}_k$$

The modified Diebold-Marino test statistic might then be written

$$DM^{ij*} = \left[\frac{N+1-2h+N^{-1}h(h-1)}{N}\right]^{\frac{1}{2}} DM^{ij}$$

where DM^{ij} is the original static in (3.1). In addition, Harvey et al. (1997) suggests to compare the test statistic with critical values from the Student's t-distribution rather than the normal distribution.

The (modified) DM is inevitable due to its simplicity and easy computation. However, it was initially intended for the setting where forecast errors (of unknown origin) rather than *models* is compared. As discussed in Teräsvirta (2006), Diebold (2015), among others, the DM-test is not valid when one parametric model nest the other. In that case, under the null of equal forecast accuracy, the errors have to be equal, such that the competing models are exactly the same. Consequently, the nominator and denominator in the DM-test statistic converge to zero at the same rate and the limit distribution of the static is non-standard, implying that the test breaks down.

This makes it problematic to use for example the AR(1) and RW model as benchmarks, because these are likely to be nested in the competing models. In this context, arguing as Teräsvirta et al. (2005), the models selecting variables with different procedures do not generally contain the same variables, and are therefore not nested. Hence, the test should be valid for comparing AR (p) with the GETS models and the penalized regression models. Moreover, the non-parametric and pure non-linear models does not nest any other model. The comparison of the GETS model with the indicator saturated GETS models is, however, problematic as the latter nests the former. As is comparing the linear AR(p) with the linear+non-linear models; the non-linear unit is not identified under the null that these two models have the same accuracy – ie that the smaller AR(p) is the true DGP. One may argue that these models approximates *different* local DGPs, in which case the accuracy of the two models might be the same, without the two being identical.

Due to these issues, two different benchmarks is selected for the uni- and multivariate case. The VAR(p) is chosen as benchmark model for the multivariate forecasts. This model is not nested in any other, since it contains up to four lags of the endogenous variables, where the remaining models only include the contemporaneous and first lag of these variables (nor in the AR(p) which in this case happen to contain more than four lags for both variables and all horizons). In the univariate case, the AR (p) model is chosen as benchmark, with the notion that the test-results in particular for the AR+ should be interpreted with care. Only test-statics comparing the remaining methods with these two benchmarks is included in the next section. The appendix include pairwise comparisons of all models, where again, one should be aware of the potential problems with nesting models.

4 Results

This section report results from the forecasting exercise. The first nowcast is made for at 2008 Q1, together with forecasts for the four next quarters. The last out-of-sample forecast is computed for 2015Q4. Hence, there is made 32, 31, 30, 29, 28 forecasts for each of the horizons, starting at $h = 0$. All forecast are made as direct forecasts, using an expanding estimation sample. The methods is compared in terms of root-mean-squared error (RMSE). The modified DM-test is used for testing the significance of the observed differences in forecast accuracy. Here, only comparisons relative to the the AR(p) benchmark in the univariate case and the vector auto-regressive (VAR)(4) in the multivariate case is reported. Test results comparing these two benchmarks is included in Annex A.2, along with their unscaled RMSEs values for each horizon. Pairwise comparisons of all methods at each horizon for both targets is reported in Annex A.3.

4.1 GDP-growth

The RMSEs for each forecasting model in forecasting the GDP-growth are reported in table 4.1. Bold values indicate the lowest RMSE for each horizon, italic the second to lowest. The univariate forecast are reported in the four rightmost column, the multivariate in the remaining. All values are relative to the linear auto-regressive benchmark: the AR(p) in the univariate case and the VAR(4) in the multivariate case. Values above 1 thus indicate a RMSE higher than the benchmark, whereas values below 1 indicate lower RMSE. The nowcasts computed at the end of the reference charter T are reported in the column denoted 0 in the table, the backcast computed one month later in column 0^*. Note that the difference in RMSE for the benchmark models in these columns and the next column (column 1) with one-step ahead forecasts is only due to the fact that the latter is based on one forecast less than the former.

Starting with the univariate forecasts, only conditioned on up to 8 real-time lags of GDP-growth, no model is best at each horizon in terms of lowest RMSE. The simple averages does, however, tend to produce the lowest RMSEs. Although, here as well, no average is *the* best at all horizons. Interestingly the average of the four benchmark models provide the lowest or second to lowest RMSE in three out of four horizons. Of the single models, the SVR with a linear kernel delivers lower RMSE in the two first horizons. For the two longest horizons, the AR(1) is the best single model. Recall that with the direct forecasting approach, this forecast is achieved regressing y_{t+4} on y_t and a constant. Only for the longest horizon, the fourth column, most model perform better than the univariate AR(p) benchmark in terms of minimum RMSE.

In the multivariate case, the model combining the AR(p) and SVR with the ANOVA RBF kernel stand out. This is the best out of all models for the two first horizons, with RMSE about 65% of the VAR(4) benchmark. For the three longest horizons, the pure

SVR models are the best, though with different kernels. The random forest provide the second to lowest RMSE for the longest horizon. In fact, this model improve relative to the benchmark as the forecast horizon increases. The GETS-models does not provide better forecasts than the VAR(4). The penalized regression models does, when tuning parameters are obtained by empirical tuning rather than information criteria. The neural network perform worse than the benchmark at all horizons.

The unscaled RMSEs values are plotted in figure 4.1 and 4.2. The linear autoregressive benchmark is plotted as a black line in these plots. Bars below this line corresponds to values below 1 in table 4.1. The lowest RMSE for each horizon is indicated with a white line. These plots suggest that there is a larger variance in RMSE across the different forecasting methods in the multivariate case compared to the univariate case. Indeed the overall lowest RMSE for all horizons is obtained when conditioning on a larger information set. That is, expanding the set of conditioning variables seems to improve the GDP forecast accuracy in terms of RMSE. The VAR(4) does, however, only provides smaller RMSE than the AR(p) for the two longest horizons.

Notably, the GETS models and the penalized regression models calibrated with the AIC provide RMSEs above the benchmark at all horizons in the multivariate case. This is not the case for the last linear learning model, the SVR-LIN. Note however, that these are not conditioned on the same information as the VAR(4). In particular, the VAR(4) contains more lags and thereby allows for more dynamics neglected in the former. The SVR with the ANOVA RBF kernel, which define the lowest RMSE in the three upper panels, does provide smaller RMSE for the one step ahead forecast compared to the now- and backcast. This suggest that the timely information does not increase the predictive accuracy of this model. One explanation may be that the conditioning variables for the $h = 0$ horizons holds higher variance, since the nowcast- and backcast made at the and one month after the end of the reference quarter include only averages of the figures available at the time, which may hold larger variance than the full figures. However, this reasoning does not hold for the pure linear models - where the RMSE tend to be lower when more information is taken into account.

Table 4.2 report test results from MDM-test comparing the forecast accuracy of the AR(p) and VAR(4) with each of the competing models. The null hypothesis tested is that the model in row i and the respective benchmark has equal predictive accuracy, ie that the expected loss differential is zero. The alternative is that the model in row i has higher predictive accuracy, that the expected loss differential is negative. Where the null is rejected at a significance level of 5% or lower, the test-static is marked in bold. Note that the benchmark models and ensemble is taken out of this table, because the models nests or is nested in the AR(p) and VAR(4). Also the AR+ models nests the AR(p).

Table 4.1: Out-sample RMSE. GDP-growth.

	Univariate				Multivariate					
	1	2	3	4	0	0*	1	2	3	4
AR(1)	1.316	0.941	**0.800**	*0.864*	1.067	1.033	1.095	0.889	0.835	0.891
RW	1.313	1.005	0.936	1.035	1.159	1.122	1.093	0.950	0.977	1.067
DDD	1.318	1.075	1.031	0.917	1.159	1.123	1.097	1.017	1.077	0.946
AR(p)	1.000	1.000	1.000	1.000	-	-	-	-	-	-
VAR(4)	-	-	-	-	1.000	1.000	1.000	1.000	1.000	1.000
GETS	1.141	1.090	1.022	0.978	1.585	1.213	1.454	1.927	1.117	2.140
GETS-IIS	1.156	1.115	1.021	0.986	1.650	1.247	1.479	1.916	1.159	2.137
GETS-SIS	1.129	1.134	1.196	1.156	1.767	1.191	1.618	2.046	1.107	2.063
GETS-DDD	1.039	1.239	1.199	1.025	1.609	1.373	1.346	1.624	1.444	1.542
GETS-IIS-DDD	1.029	1.242	1.200	1.026	1.616	1.254	1.433	1.661	1.450	1.552
GETS-SIS-DDD	1.028	1.234	1.166	1.018	1.709	1.287	1.380	1.658	1.458	1.408
Ridge, CV	1.034	1.005	1.013	0.952	0.841	0.808	0.964	0.650	0.819	0.878
Lasso, CV	1.018	1.005	1.021	0.965	0.850	0.806	1.023	0.667	0.928	0.898
ELNET, CV	1.021	1.011	1.021	0.961	0.827	0.791	0.969	0.679	0.933	0.901
Ridge, AIC	1.016	0.994	1.019	0.952	1.157	1.074	1.408	1.065	0.761	1.229
Lasso, AIC	1.002	1.006	1.017	0.956	1.919	1.897	1.787	2.032	2.031	2.060
ELNET, AIC	1.002	1.002	1.032	0.950	1.938	1.977	2.141	2.281	1.929	2.146
k-NN	1.483	1.241	1.032	0.943	0.877	1.029	0.905	1.454	1.108	1.056
wk-NN	1.516	1.261	0.957	0.881	0.848	0.933	0.976	1.228	1.013	0.942
RF	1.160	0.957	0.976	0.914	1.133	1.093	0.852	0.736	0.772	*0.773*
FFNN	1.068	1.063	1.058	0.897	1.063	1.033	1.223	1.061	0.713	1.084
RNN	1.056	1.128	1.203	0.957	1.497	1.935	1.420	1.299	1.002	1.222
SVR-LIN	0.989	*0.938*	1.031	1.001	0.801	0.834	0.902	*0.594*	**0.559**	0.870
SVR-POLY	1.052	0.990	1.306	0.985	0.858	0.921	1.120	0.694	*0.585*	**0.662**
SVR-RBF	1.099	1.081	1.088	1.021	0.980	0.957	0.979	0.812	0.708	0.784
SVR-ANOVA	1.086	1.044	1.082	1.205	0.891	0.903	1.023	**0.547**	1.079	0.919
AR+SVR-POLY	1.055	0.997	0.971	0.966	0.712	0.682	*0.756*	0.786	1.034	1.031
AR+SVR-RBF	1.088	1.024	0.972	0.972	0.768	0.753	0.781	0.888	0.916	1.021
AR+SVR-ANOVA	1.015	0.987	0.948	1.023	**0.658**	**0.651**	**0.636**	0.798	0.933	1.027
AR+FFNN	0.997	1.002	0.999	0.996	0.800	0.845	0.908	1.035	0.802	1.089
AR+RNN	1.102	1.227	1.301	1.216	0.986	0.927	1.722	1.710	1.656	1.299
Ave. BM	1.176	**0.918**	*0.863*	**0.803**	0.957	0.934	0.979	0.867	0.901	0.828
Ave. Linear	*0.967*	0.950	0.954	0.885	1.250	0.999	1.189	1.221	0.913	1.305
Ave. Local	1.352	1.114	0.960	0.900	0.897	0.961	0.878	1.074	0.895	0.876
Ave. Non-linear	0.985	0.999	1.046	0.976	0.860	0.947	0.981	0.784	0.640	0.803
Ave. AR+	**0.934**	0.946	0.953	0.939	*0.695*	*0.679*	0.782	0.924	0.965	0.971
Tot. Ave.	0.974	0.941	0.942	0.892	0.850	0.745	0.873	0.897	0.690	1.003

Note: *Computed one month after end of reference quarter. RMSE relative to the AR(p) benchmark in the univariate case and VAR(4) in the multivariate. **Bold** denotes the lowest RMSE for each horizon, *italic* the second to lowest.

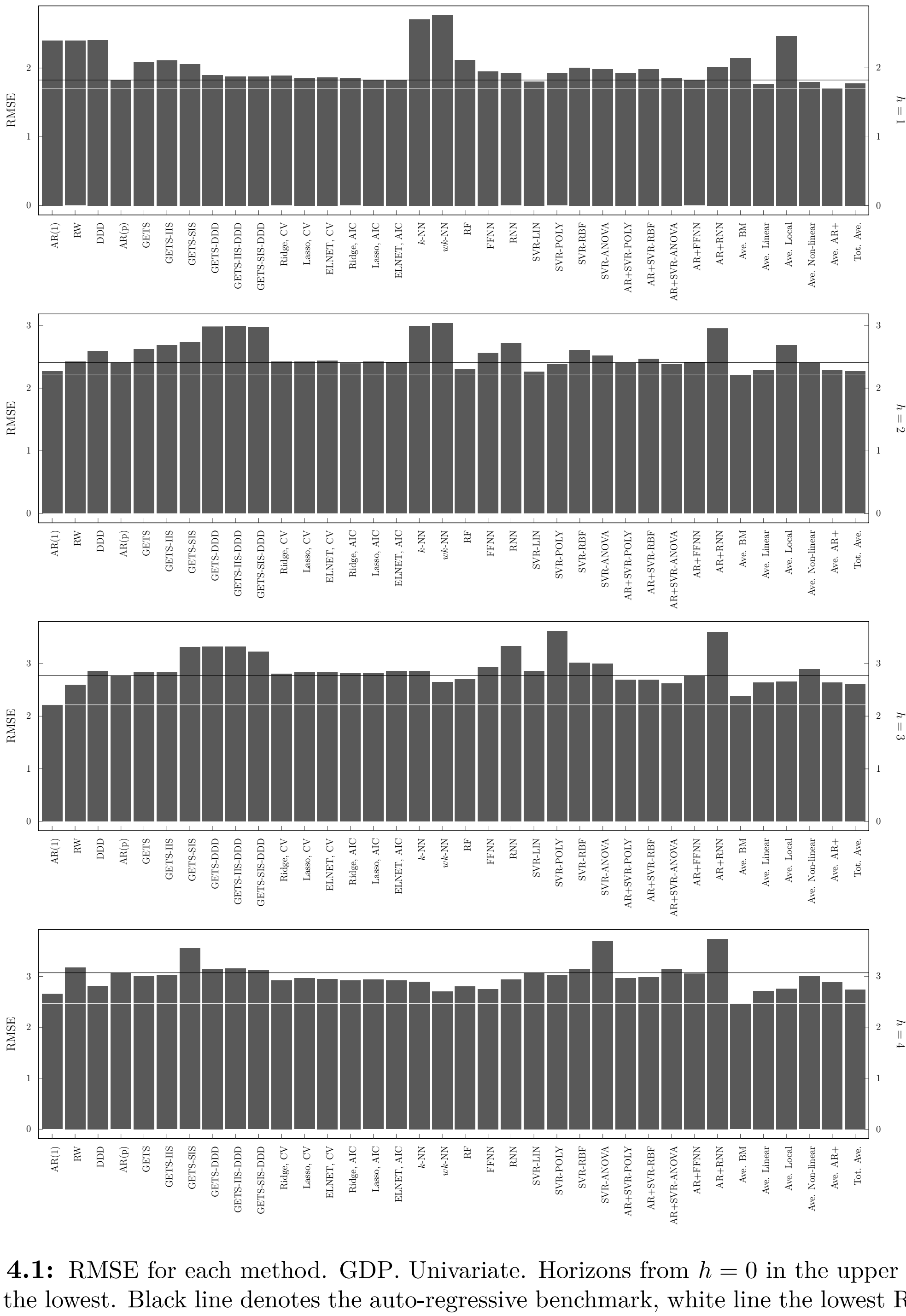

Figure 4.1: RMSE for each method. GDP. Univariate. Horizons from $h = 0$ in the upper panel to $h = 4$ in the lowest. Black line denotes the auto-regressive benchmark, white line the lowest RMSE at each horizon.

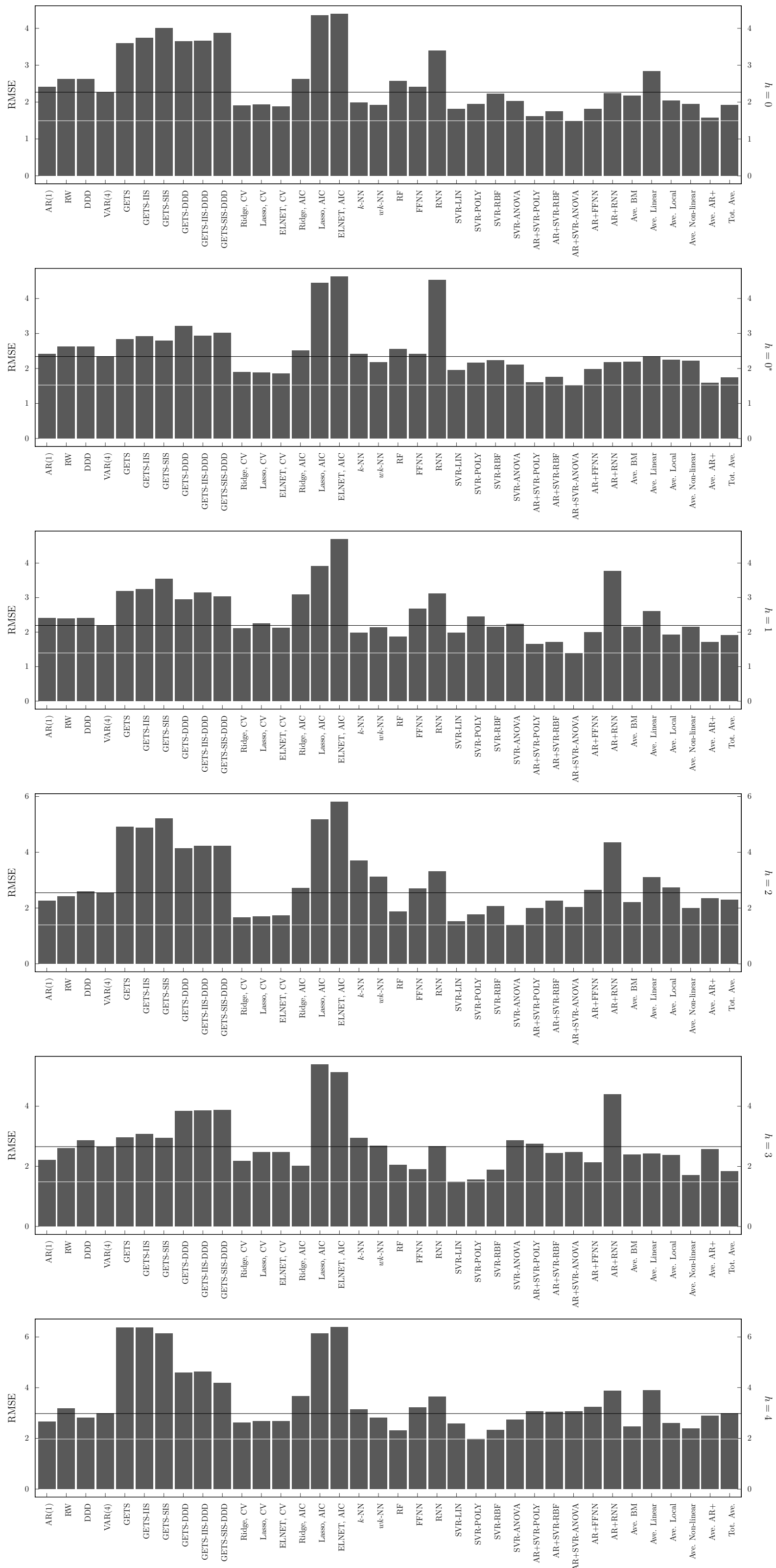

Figure 4.2: RMSE for each method. GDP. Multivariate. Horizons from $h = 0$ in the two upper panels to $h = 4$ in the lowest. Black line denotes the auto-regressive benchmark, white line the lowest RMSE at each horizon.

Table 4.2: Modified Diebold-Marino test for equal forecast accuracy. GDP-growth.

	Univariate				Multivariate					
	1	2	3	4	0	0*	1	2	3	4
GETS	1.715	1.969	0.819	-0.883	1.638	1.151	1.261	1.495	0.407	1.139
	(0.952)	(0.971)	(0.790)	(0.193)	(0.944)	(0.871)	(0.891)	(0.927)	(0.656)	(0.868)
GETS-IIS	2.002	2.339	1.217	-0.878	1.836	1.303	1.242	1.478	0.511	1.160
	(0.973)	(0.987)	(0.883)	(0.194)	(0.962)	(0.899)	(0.888)	(0.925)	(0.693)	(0.872)
GETS-SIS	1.409	1.501	1.518	1.019	1.785	0.827	1.433	1.441	0.357	1.284
	(0.915)	(0.928)	(0.930)	(0.841)	(0.958)	(0.793)	(0.919)	(0.920)	(0.638)	(0.895)
GETS-DDD	0.244	1.072	1.985	0.187	1.533	1.451	1.114	2.686	3.561	1.474
	(0.595)	(0.854)	(0.971)	(0.574)	(0.932)	(0.922)	(0.863)	(0.994)	(0.999)	(0.924)
GETS-IIS-DDD	0.187	1.060	2.198	0.194	1.552	1.328	1.107	2.598	2.954	1.483
	(0.573)	(0.851)	(0.982)	(0.576)	(0.935)	(0.903)	(0.861)	(0.993)	(0.997)	(0.925)
GETS-SIS-DDD	0.178	1.052	1.892	0.150	1.594	1.163	1.129	2.497	2.897	1.611
	(0.570)	(0.849)	(0.966)	(0.559)	(0.940)	(0.873)	(0.866)	(0.991)	(0.996)	(0.941)
Ridge, CV	1.418	0.279	0.366	-1.296	-1.032	-1.326	-0.260	-1.373	**-7.987**	-1.049
	(0.917)	(0.609)	(0.641)	(0.103)	(0.155)	(0.097)	(0.398)	(0.090)	**(0.000)**	(0.152)
Lasso, CV	1.280	0.212	0.562	-1.246	-1.112	-1.382	0.156	**-1.851**	-0.345	-0.887
	(0.895)	(0.583)	(0.711)	(0.112)	(0.137)	(0.088)	(0.562)	**(0.037)**	(0.366)	(0.192)
ELNET, CV	1.504	0.649	0.553	-1.342	-1.204	-1.394	-0.223	**-1.798**	-0.325	-0.901
	(0.929)	(0.739)	(0.708)	(0.095)	(0.119)	(0.087)	(0.413)	**(0.041)**	(0.374)	(0.188)
Ridge, AIC	0.917	-0.528	0.758	-1.503	0.669	0.333	1.232	0.231	**-1.877**	1.038
	(0.817)	(0.301)	(0.773)	(0.072)	(0.746)	(0.629)	(0.886)	(0.590)	**(0.035)**	(0.846)
Lasso, AIC	1.320	0.368	0.469	-1.585	2.279	2.478	1.415	1.216	0.994	1.733
	(0.902)	(0.642)	(0.679)	(0.062)	(0.985)	(0.991)	(0.916)	(0.883)	(0.836)	(0.953)
ELNET, AIC	1.113	0.096	1.063	-1.431	2.345	2.470	2.044	1.171	1.024	1.789
	(0.863)	(0.538)	(0.852)	(0.082)	(0.987)	(0.990)	(0.975)	(0.874)	(0.843)	(0.958)
k-NN	2.880	2.475	0.470	-0.680	-0.657	0.158	-0.821	2.928	0.539	0.251
	(0.996)	(0.990)	(0.679)	(0.251)	(0.258)	(0.562)	(0.209)	(0.997)	(0.703)	(0.598)
wk-NN	2.310	1.705	-0.881	-1.249	-0.928	-0.450	-0.177	1.871	0.091	-0.404
	(0.986)	(0.951)	(0.193)	(0.111)	(0.180)	(0.328)	(0.430)	(0.964)	(0.536)	(0.345)
RF	0.987	-0.354	-0.410	-0.938	0.937	0.687	-0.958	**-4.908**	**-2.220**	**-1.728**
	(0.834)	(0.363)	(0.343)	(0.178)	(0.822)	(0.751)	(0.173)	**(0.000)**	**(0.017)**	**(0.048)**
FFNN	0.831	0.619	0.911	-0.952	0.303	0.166	1.043	0.202	-1.150	0.707
	(0.794)	(0.730)	(0.815)	(0.175)	(0.618)	(0.565)	(0.847)	(0.580)	(0.130)	(0.757)
RNN	0.764	1.048	1.518	-0.353	3.074	2.816	2.977	1.932	4.277	2.595
	(0.775)	(0.848)	(0.930)	(0.364)	(0.998)	(0.996)	(0.997)	(0.968)	(1.000)	(0.992)
SVR-LIN	-0.263	-1.078	0.529	0.038	-1.384	-1.255	-0.434	**-1.706**	**-2.072**	-1.573
	(0.397)	(0.145)	(0.699)	(0.515)	(0.088)	(0.109)	(0.334)	**(0.049)**	**(0.024)**	(0.064)
SVR-POLY	0.627	-0.312	1.231	-0.369	-0.874	-0.515	0.590	**-1.747**	**-2.063**	-1.544
	(0.732)	(0.379)	(0.886)	(0.357)	(0.195)	(0.305)	(0.720)	**(0.046)**	**(0.024)**	(0.067)
SVR-RBF	0.758	0.828	1.093	0.277	-0.136	-0.307	-0.217	-1.347	**-2.687**	-1.652
	(0.773)	(0.793)	(0.858)	(0.608)	(0.446)	(0.380)	(0.415)	(0.094)	**(0.006)**	(0.055)
SVR-ANOVA	0.846	0.901	1.405	0.996	-0.811	-0.696	0.117	**-2.445**	0.237	-0.798
	(0.798)	(0.812)	(0.914)	(0.836)	(0.212)	(0.246)	(0.546)	**(0.010)**	(0.593)	(0.216)
AR+SVR-POLY	1.233	-0.032	-0.271	-0.229	-1.603	**-1.782**	-1.036	-1.097	0.193	0.193
	(0.886)	(0.487)	(0.394)	(0.410)	(0.060)	**(0.042)**	(0.154)	(0.141)	(0.576)	(0.576)
AR+SVR-RBF	0.889	0.352	-0.267	-0.199	-1.293	-1.393	-1.197	-0.992	-0.749	0.189
	(0.809)	(0.636)	(0.396)	(0.422)	(0.103)	(0.087)	(0.120)	(0.165)	(0.230)	(0.574)
AR+SVR-ANOVA	0.454	-0.181	-0.554	0.187	**-1.951**	**-2.031**	-1.610	-1.008	-0.533	0.146
	(0.673)	(0.429)	(0.292)	(0.574)	**(0.030)**	**(0.025)**	(0.059)	(0.161)	(0.299)	(0.558)
AR+FFNN	-0.114	0.023	-0.016	-0.024	-0.930	-0.735	-0.388	0.137	-0.945	0.422
	(0.455)	(0.509)	(0.494)	(0.491)	(0.180)	(0.234)	(0.350)	(0.554)	(0.176)	(0.662)
AR+RNN	0.520	1.384	1.229	0.677	-0.058	-0.359	3.174	2.283	1.955	1.568
	(0.696)	(0.912)	(0.885)	(0.748)	(0.477)	(0.361)	(0.998)	(0.985)	(0.970)	(0.936)
Ave. Linear	-0.994	-0.896	**-1.869**	-1.247	0.851	-0.006	0.570	0.797	-0.526	0.874
	(0.164)	(0.189)	**(0.036)**	(0.112)	(0.799)	(0.498)	(0.714)	(0.784)	(0.302)	(0.805)
Ave. Local	2.027	0.862	-0.771	-1.074	-0.756	-0.306	-0.928	0.548	-1.008	-0.877
	(0.974)	(0.802)	(0.224)	(0.146)	(0.228)	(0.381)	(0.180)	(0.706)	(0.161)	(0.194)
Ave. Non-linear	-0.248	-0.023	0.751	-0.871	-0.956	-0.384	-0.104	-1.129	**-2.057**	-1.434
	(0.403)	(0.491)	(0.770)	(0.196)	(0.173)	(0.352)	(0.459)	(0.134)	**(0.025)**	(0.082)
Ave. AR+	-1.060	-0.626	-0.420	-0.367	-1.513	-1.629	-1.016	-0.427	-0.246	-0.173
	(0.149)	(0.268)	(0.339)	(0.358)	(0.070)	(0.057)	(0.159)	(0.336)	(0.404)	(0.432)
Tot. Ave.	-0.728	-1.252	**-2.862**	-1.364	-0.725	-1.301	-0.738	-1.277	**-2.383**	-0.537
	(0.236)	(0.110)	**(0.004)**	(0.092)	(0.237)	(0.101)	(0.233)	(0.106)	**(0.012)**	(0.298)

Note: *Computed one month after end of reference quarter. This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and the AR(p) (univariate case) or VAR(4) (multivariate case) has equal predictive accuracy. The loss function used is the squared errors. The alternative is that the method is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

For these models the test is valid only under the assumption that the AR(p) is not the data-generating process. In the univariate case, only the average of the linear models and of all machine learning models has higher predictive accuracy than the AR(p) model, and only for the three step ahead forecasts, according to the DM-test. In the multivariate case, the test suggest that nowcasts produced with the two of the AR+SVR models has indeed higher predictive accuracy than the VAR(4). For the three longest horizons, this holds for the random forest, which was never the best model in terms of RMSE, but the second to best for the longest horizon. Some of the SVR-models are more accurate at the second and third horizon, as is certain penalized regression models. The average of the non-linear models and the total average has lower predictive accuracy when forecasting three steps ahead.

4.2 Inflation

Table 4.3 report RMSEs for the inflation rate. Again, the lowest RMSE for each horizon is marked in bold, the second to lowest in italic and all values are relative to the linear auto-regressive benchmark.

As in the case of GDP-growth, no single forecast method perform best at every horizon. The average of the benchmark models does, however, most often produce the lowest RMSE. In the univariate case, the best single model is one of the linear models at each horizon. In particular, the GETS model provide the lowest or second to lowest RMSE for the two first horizons. Neither this, nor any other model, beat the AR(p) benchmark at all horizons.

In the multivariate case, GETS with and without IIS provides the best nowcast at the end of the quarter. Remember that the CPI figures for the two first months are known and included at the right hand side at this point (not in the benchmark models). The lowest RMSE among the one-step-ahead forecasts is provided by the SVR-RBF model. At two next horizon, the average benchmark models is the best in terms of RMSE. At the longest horizon, the random forest provide the lowest RMSE. Again, this model improve relative to the benchmark for the longer horizons. The nearest neighbours models provide surprisingly low RMSEs at the longest horizon, and the average of the local models does in fact provides the second to lowest RMSE at this horizon.

The RMSEs are plotted in figure 4.3 and figure 4.4. Again, the black line denotes the benchmark RMSE, the white line the lowest. In the multivariate case, the penalized regression models seems to perform best of the linear models, and provide RMSEs lower than the VAR(4) for the two longest horizons. Most of the averages except the average of the linear models provide lower RMSEs than the benchmark at each horizon. Of the single models, this is the case only for the SVR-RBF model, the random forest and the AR(1). Not obvious from these plots, the AR(p) provides lower mean squared errors than the multivariate benchmark at all horizons, see table A.2.2 in Annex A.2.

Table 4.4 report results from the MDM-test. In the linear case, the only model providing more accurate forecasts than the AR(p) model is the GETS model, and only for the second horizon. Close to every method provide more accurate nowcasts compared to the one-step ahead forecasts obtained with the VAR(4), which is reasonable since these include the CPI-figures from the two first months of the quarter. For the fourth horizon, ridge regression, the local methods and two of the ensembles are more accurate than the VAR(4) according to the this test.

Overall, the results indicate that there are no single model that provide superior forecast. Rather, the best model in terms of RMSE seems to depend on the horizon, the target and the conditioning information. The benchmark models are, nevertheless, hard to beat, confirmed by the modified DM test which indicate that the cases where the machine learning models provide more accurate forecast is the exception, not the rule. In the case of GDP different SVR approaches seems to do the best, also according to the modified DM-test. In forecasting inflation, the simple average of the benchmark models does notably well. Also the random forest holds significantly higher predictive accuracy than the benchmark at the longest horizon. In terms of minimum RMSE there seems to be accuracy gains from including a rather extensive set of conditioning variables, at least for most of the models, when forecasting GDP-growth. In forecasting the inflation rate this is not that obvious. The simple univariate AR(1) is one out of three models that provide RMSE lower than the VAR(4) benchmark for all horizons. No formal comparison between the uni- and multivariate forecasts is undertaken, except for the two auto-regressive benchmarks: the univariate model provide the lowest RMSEs for all horizons for inflation. In the case of GDP this holds for the two shortest horizons. The MDM-test does, however, not reject the null that these models have equal predictive accuracy. These results are reported in Annex A.2.

Table 4.5 and 4.6 compare the RMSEs from the multivariate models across different sub-samples for GDP-growth and inflation, respectively. Note that scales of plots the left panel, based on forecast errors from the financial crisis, are larger than those in the right panel. For the GDP-growth, the distribution of mean squared forecast errors seems to be quite similar across the two sub-samples. Notably, the RNN and the local methods has higher RMSEs in the last period. For the inflation rate, there are some differences across the two sub-samples, in particular for the longest horizons. The benchmark VAR(4) model is much closer to the lowest RMSE for all horizons in the last period.

Table 4.3: Inflation. Out-sample RMSE

	Univariate				Multivariate				
	1	2	3	4	0	1	2	3	4
AR(1)	1.057	1.014	0.938	1.009	0.946	0.877	0.899	0.839	0.818
RW	1.140	1.094	0.987	1.310	1.027	0.947	0.969	0.883	1.063
DDD	1.555	1.196	0.985	1.247	1.262	1.291	1.059	0.882	1.012
AR(p)	1.000	1.000	1.000	1.000	-	-	-	-	-
VAR(4)	-	-	-	-	1.000	1.000	1.000	1.000	1.000
GETS	**0.993**	0.978	0.977	1.078	*0.281*	1.313	1.612	1.390	1.664
GETS-IIS	1.043	1.004	1.051	1.076	**0.277**	1.216	1.545	1.430	1.626
GETS-SIS	1.146	1.042	1.240	1.580	0.424	1.313	1.563	1.496	1.757
GETS-DDD	1.334	1.369	1.110	1.332	0.442	1.519	1.443	1.635	1.782
GETS-IIS-DDD	1.384	1.450	1.232	1.393	0.346	1.430	1.383	1.590	1.701
GETS-SIS-DDD	1.285	1.338	1.110	1.377	0.446	1.431	1.417	1.561	1.599
Ridge, CV	1.039	1.235	1.020	*0.895*	0.489	0.920	1.146	0.964	0.768
Lasso, CV	1.047	1.241	1.026	0.949	0.293	1.046	1.194	0.864	0.725
ELNET, CV	1.045	1.238	1.023	0.946	0.296	0.965	1.477	0.927	0.719
Ridge, AIC	1.006	1.028	0.984	1.098	0.467	1.057	1.217	1.234	1.167
Lasso, AIC	*0.994*	1.016	0.977	1.060	0.295	1.317	1.747	1.606	1.754
ELNET, AIC	1.000	1.033	0.977	1.053	0.291	1.428	1.828	1.628	1.714
k-NN	1.351	1.506	1.448	1.244	0.942	0.932	1.224	1.078	0.709
wk-NN	1.361	1.478	1.423	1.298	0.945	0.917	1.246	1.115	0.700
RF	1.114	1.115	0.963	0.965	0.403	1.013	0.981	0.798	**0.628**
FFNN	1.141	1.082	0.996	1.049	0.439	0.945	1.000	0.952	0.856
RNN	1.219	1.506	1.227	1.975	0.845	1.277	1.117	1.387	1.446
SVR-LIN	1.096	1.007	1.061	1.053	0.495	1.012	1.549	1.141	0.946
SVR-POLY	1.365	1.068	1.348	1.346	0.540	1.271	1.052	0.911	0.934
SVR-RBF	1.421	1.325	1.116	1.075	0.672	**0.795**	0.963	*0.715*	0.709
SVR-ANOVA	1.289	1.378	1.347	1.214	0.603	1.373	1.540	1.112	1.636
AR+SVR-POLY	1.174	1.198	1.232	1.113	0.604	1.046	*0.874*	0.918	0.873
AR+SVR-RBF	1.119	1.156	1.195	1.428	0.793	0.931	0.920	0.916	0.770
AR+SVR-ANOVA	1.014	*0.970*	1.154	1.400	0.543	*0.870*	1.205	0.969	1.138
AR+FFNN	1.008	1.222	1.192	1.068	0.630	1.018	0.936	0.993	0.951
AR+RNN	1.140	1.383	1.489	1.114	1.129	1.207	1.128	1.246	1.216
Ave. BM	1.055	**0.928**	**0.752**	**0.882**	0.966	0.931	**0.848**	**0.689**	0.729
Ave. Linear	1.017	1.010	*0.859*	0.944	0.319	1.096	1.267	1.146	1.127
Ave. Local	1.197	1.308	1.224	1.090	0.690	0.892	1.067	0.936	*0.638*
Ave. Non-linear	1.079	1.120	1.061	1.165	0.502	0.970	0.911	0.744	0.747
Ave. AR+	1.024	1.090	1.171	1.080	0.685	0.907	0.909	0.938	0.843
Tot. Ave.	1.006	1.037	0.956	0.981	0.448	0.910	0.946	0.858	0.773

Note: RMSE relative to the AR(p) benchmark in the univariate case and VAR(4) in the multivariate. **Bold** denotes the lowest RMSE for each horizon, *italic* the second to lowest.

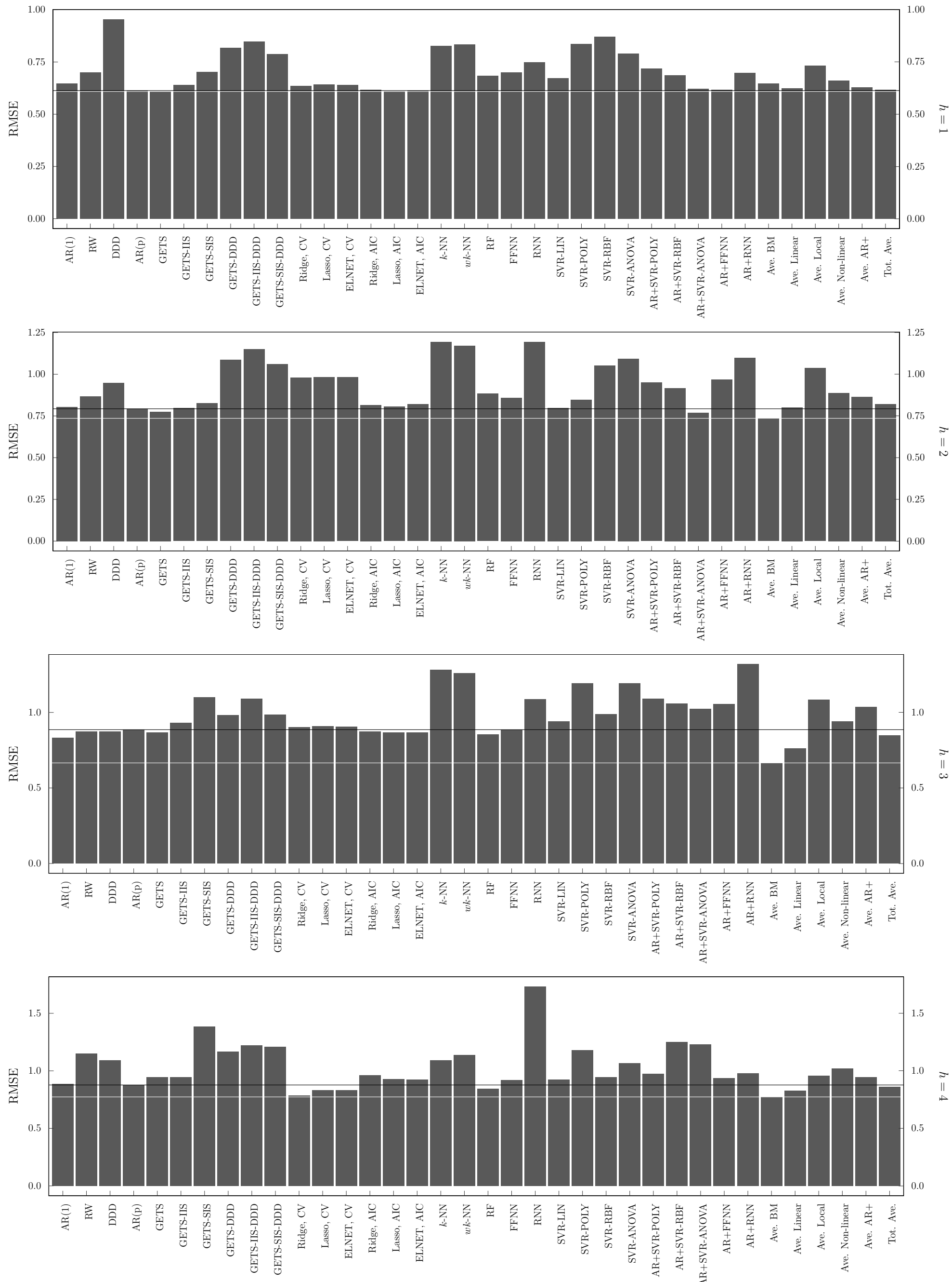

Figure 4.3: RMSE for each method. CPI. Univariate. Horizons from $h = 0$ in the upper panel to $h = 4$ in the lowest. Black line denotes the auto-regressive benchmark, white line the lowest RMSE at each horizon.

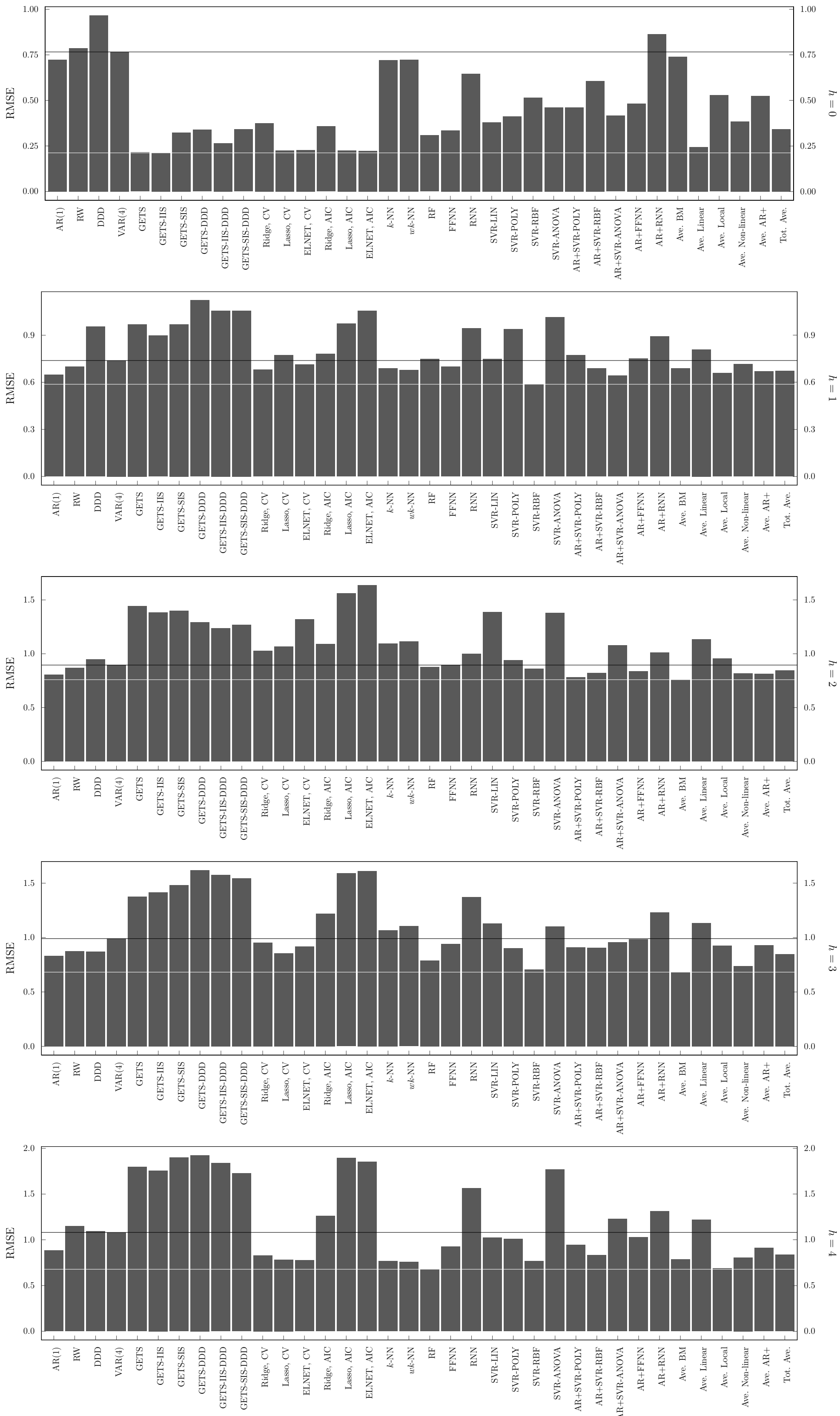

Figure 4.4: RMSE for each method. CPI. Multivariate. Horizons from $h = 0$ in the upper panel to $h = 4$ in the lowest. Black line denotes the auto-regressive benchmark, white line the lowest RMSE at each horizon.

Table 4.4: Diebold-Marino test for equal forecast accuracy. Inflation.

	Univariate				Multivariate				
	1	2	3	4	0	1	2	3	4
GETS	-0.163	**-2.177**	-1.619	0.882	**-2.648**	1.230	1.314	2.396	1.254
	(0.436)	**(0.019)**	(0.058)	(0.807)	**(0.006)**	(0.886)	(0.900)	(0.988)	(0.890)
GETS-IIS	0.480	0.074	0.981	0.655	**-2.658**	0.874	1.245	3.093	1.434
	(0.683)	(0.529)	(0.833)	(0.741)	**(0.006)**	(0.806)	(0.888)	(0.998)	(0.919)
GETS-SIS	1.164	0.287	1.017	2.768	**-2.328**	1.601	1.067	3.254	2.205
	(0.873)	(0.612)	(0.841)	(0.995)	**(0.013)**	(0.940)	(0.853)	(0.999)	(0.982)
GETS-DDD	2.244	1.490	0.457	1.016	**-2.271**	2.609	1.567	2.076	1.354
	(0.984)	(0.927)	(0.674)	(0.841)	**(0.015)**	(0.993)	(0.936)	(0.976)	(0.907)
GETS-IIS-DDD	2.291	1.642	0.948	1.097	**-2.495**	2.166	1.309	2.027	1.460
	(0.985)	(0.944)	(0.824)	(0.859)	**(0.009)**	(0.981)	(0.900)	(0.974)	(0.922)
GETS-SIS-DDD	2.260	1.449	0.463	1.063	**-2.260**	2.176	1.374	1.600	1.542
	(0.984)	(0.921)	(0.677)	(0.851)	**(0.016)**	(0.981)	(0.910)	(0.940)	(0.933)
Ridge, CV	0.725	1.648	0.552	-1.448	**-2.424**	-0.669	0.821	-0.416	**-1.811**
	(0.763)	(0.945)	(0.707)	(0.080)	**(0.011)**	(0.254)	(0.791)	(0.340)	**(0.041)**
Lasso, CV	0.705	1.846	0.750	-0.820	**-2.691**	0.572	1.008	-1.038	-1.628
	(0.757)	(0.962)	(0.770)	(0.210)	**(0.006)**	(0.714)	(0.839)	(0.154)	(0.058)
ELNET, CV	0.684	1.805	0.697	-0.840	**-2.688**	-0.380	1.154	-0.550	-1.661
	(0.750)	(0.959)	(0.754)	(0.204)	**(0.006)**	(0.353)	(0.871)	(0.293)	(0.054)
Ridge, AIC	0.131	0.887	-1.060	1.226	**-2.496**	0.290	1.057	0.995	0.556
	(0.552)	(0.809)	(0.149)	(0.885)	**(0.009)**	(0.613)	(0.850)	(0.836)	(0.709)
Lasso, AIC	-0.143	0.569	-0.905	0.719	**-2.678**	1.033	1.587	1.810	1.194
	(0.444)	(0.713)	(0.187)	(0.761)	**(0.006)**	(0.845)	(0.938)	(0.959)	(0.879)
ELNET, AIC	0.011	1.159	-0.891	0.618	**-2.680**	1.119	1.645	1.735	1.283
	(0.504)	(0.872)	(0.190)	(0.729)	**(0.006)**	(0.864)	(0.945)	(0.953)	(0.895)
k-NN	2.254	2.357	2.447	1.096	-0.317	-0.359	0.863	0.726	**-1.787**
	(0.984)	(0.987)	(0.990)	(0.859)	(0.377)	(0.361)	(0.802)	(0.763)	**(0.043)**
wk-NN	2.392	1.978	2.134	1.267	-0.302	-0.416	1.557	1.166	**-1.718**
	(0.988)	(0.971)	(0.979)	(0.892)	(0.382)	(0.340)	(0.935)	(0.873)	**(0.049)**
RF	1.263	1.109	-0.558	-0.263	**-2.449**	0.092	-0.106	-1.616	**-2.743**
	(0.892)	(0.862)	(0.291)	(0.397)	**(0.010)**	(0.536)	(0.458)	(0.059)	**(0.005)**
FFNN	1.511	1.152	-0.110	0.394	**-2.315**	-0.422	0.002	-0.359	-0.826
	(0.929)	(0.871)	(0.456)	(0.652)	**(0.014)**	(0.338)	(0.501)	(0.361)	(0.208)
RNN	2.168	2.806	1.346	1.788	-0.898	1.352	0.532	1.664	2.037
	(0.981)	(0.996)	(0.905)	(0.958)	(0.188)	(0.907)	(0.701)	(0.946)	(0.974)
SVR-LIN	1.522	0.143	0.864	0.956	**-2.261**	0.097	0.958	0.723	-0.281
	(0.931)	(0.557)	(0.803)	(0.826)	**(0.015)**	(0.539)	(0.827)	(0.762)	(0.390)
SVR-POLY	1.257	0.849	0.977	0.948	**-2.281**	0.753	0.387	-0.734	-0.313
	(0.891)	(0.798)	(0.831)	(0.824)	**(0.015)**	(0.771)	(0.649)	(0.234)	(0.378)
SVR-RBF	1.895	1.844	1.046	0.788	**-1.943**	-1.337	-0.211	-1.373	-1.234
	(0.966)	(0.962)	(0.848)	(0.781)	**(0.031)**	(0.096)	(0.417)	(0.090)	(0.114)
SVR-ANOVA	2.067	2.852	1.670	0.862	**-1.896**	1.078	1.564	0.754	0.982
	(0.976)	(0.996)	(0.947)	(0.802)	**(0.034)**	(0.855)	(0.936)	(0.772)	(0.832)
AR+SVR-POLY	0.999	2.278	1.256	1.537	**-1.975**	0.299	-0.742	-0.578	-0.835
	(0.837)	(0.985)	(0.890)	(0.932)	**(0.029)**	(0.617)	(0.232)	(0.284)	(0.206)
AR+SVR-RBF	1.833	1.292	1.992	2.165	-1.245	-0.404	-0.442	-0.431	-1.456
	(0.962)	(0.897)	(0.972)	(0.980)	(0.111)	(0.344)	(0.331)	(0.335)	(0.078)
AR+SVR-ANOVA	0.396	-0.314	0.923	1.327	**-2.056**	-0.911	0.907	-0.350	0.722
	(0.653)	(0.378)	(0.818)	(0.902)	**(0.024)**	(0.185)	(0.814)	(0.365)	(0.762)
AR+FFNN	1.029	1.652	1.511	1.083	**-2.021**	0.099	-0.371	-0.056	-0.310
	(0.844)	(0.945)	(0.929)	(0.856)	**(0.026)**	(0.539)	(0.357)	(0.478)	(0.379)
AR+RNN	1.390	2.084	1.789	1.273	0.697	1.192	0.614	2.618	1.133
	(0.913)	(0.977)	(0.958)	(0.893)	(0.754)	(0.879)	(0.728)	(0.993)	(0.867)
Ave. Linear	0.483	0.148	-1.396	-0.535	**-2.613**	0.528	0.954	1.155	0.560
	(0.684)	(0.558)	(0.087)	(0.299)	**(0.007)**	(0.699)	(0.826)	(0.871)	(0.710)
Ave. Local	1.568	1.799	1.793	0.703	-1.653	-0.610	0.335	-0.895	**-2.457**
	(0.936)	(0.959)	(0.958)	(0.756)	(0.054)	(0.273)	(0.630)	(0.189)	**(0.010)**
Ave. Non-linear	1.295	1.488	1.200	1.288	**-2.379**	-0.192	-0.374	-1.308	-1.397
	(0.897)	(0.926)	(0.880)	(0.896)	**(0.012)**	(0.425)	(0.356)	(0.101)	(0.087)
Ave. AR+	0.791	1.313	1.903	3.986	-1.695	-0.630	-0.480	-0.475	-0.926
	(0.782)	(0.900)	(0.966)	(1.000)	(0.050)	(0.267)	(0.317)	(0.319)	(0.181)
Tot. Ave.	0.253	1.141	-1.443	-0.432	**-2.554**	-0.629	-0.268	-1.084	**-1.914**
	(0.599)	(0.868)	(0.080)	(0.334)	**(0.008)**	(0.267)	(0.395)	(0.144)	**(0.033)**

Note: *Computed one month after end of reference quarter. This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and the AR(p) (univariate case) or VAR(4) (multivariate case) has equal predictive accuracy. The loss function used is the squared errors. The alternative is that the method is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

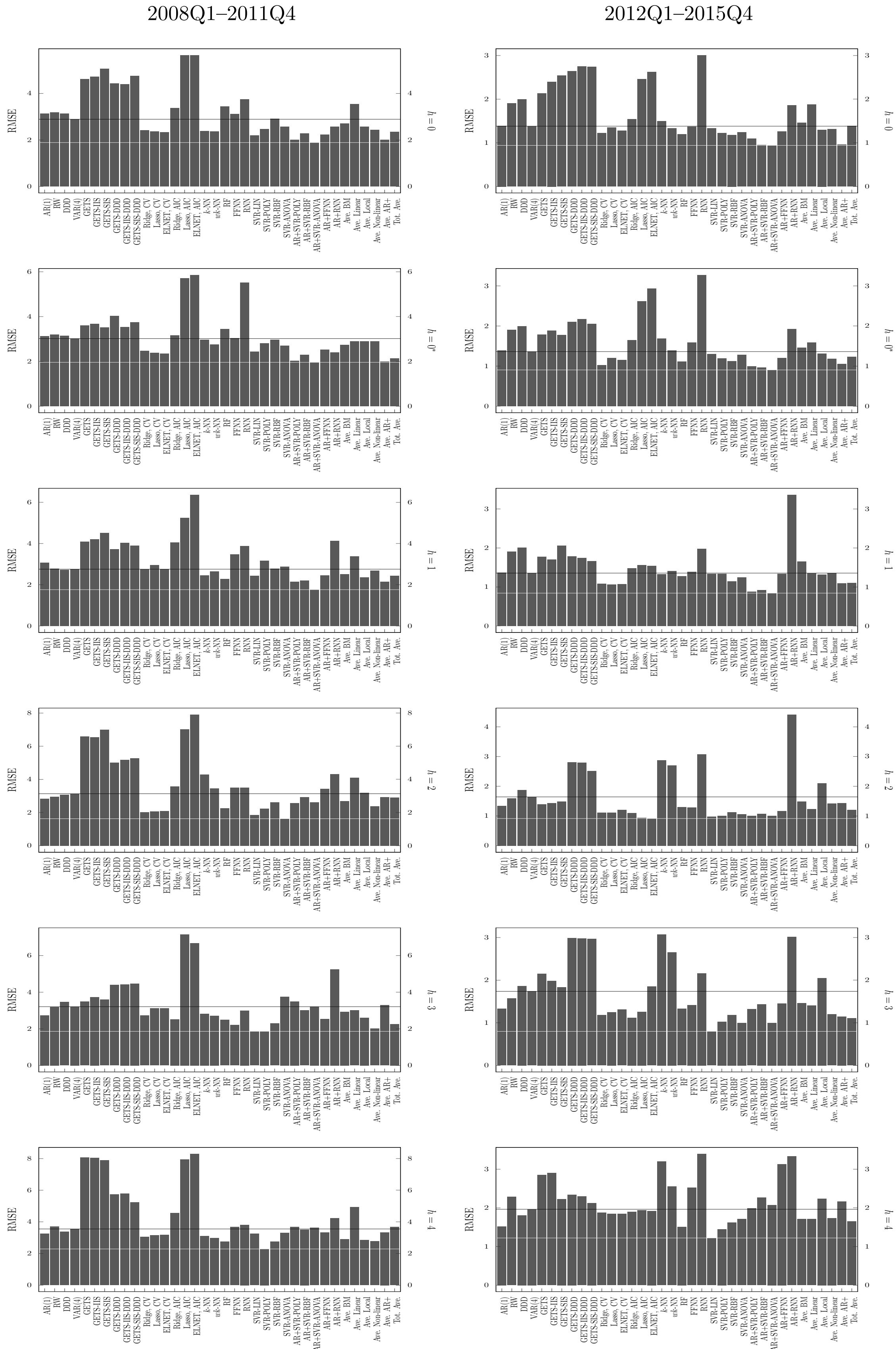

Figure 4.5: RMSE in different parts of the out-sample. GDP. Multivariate. Horizons from $h = 0$ in the upper panel to $h = 4$ in the lowest. Black line denotes the auto-regressive benchmark, white line the lowest RMSE at each horizon.

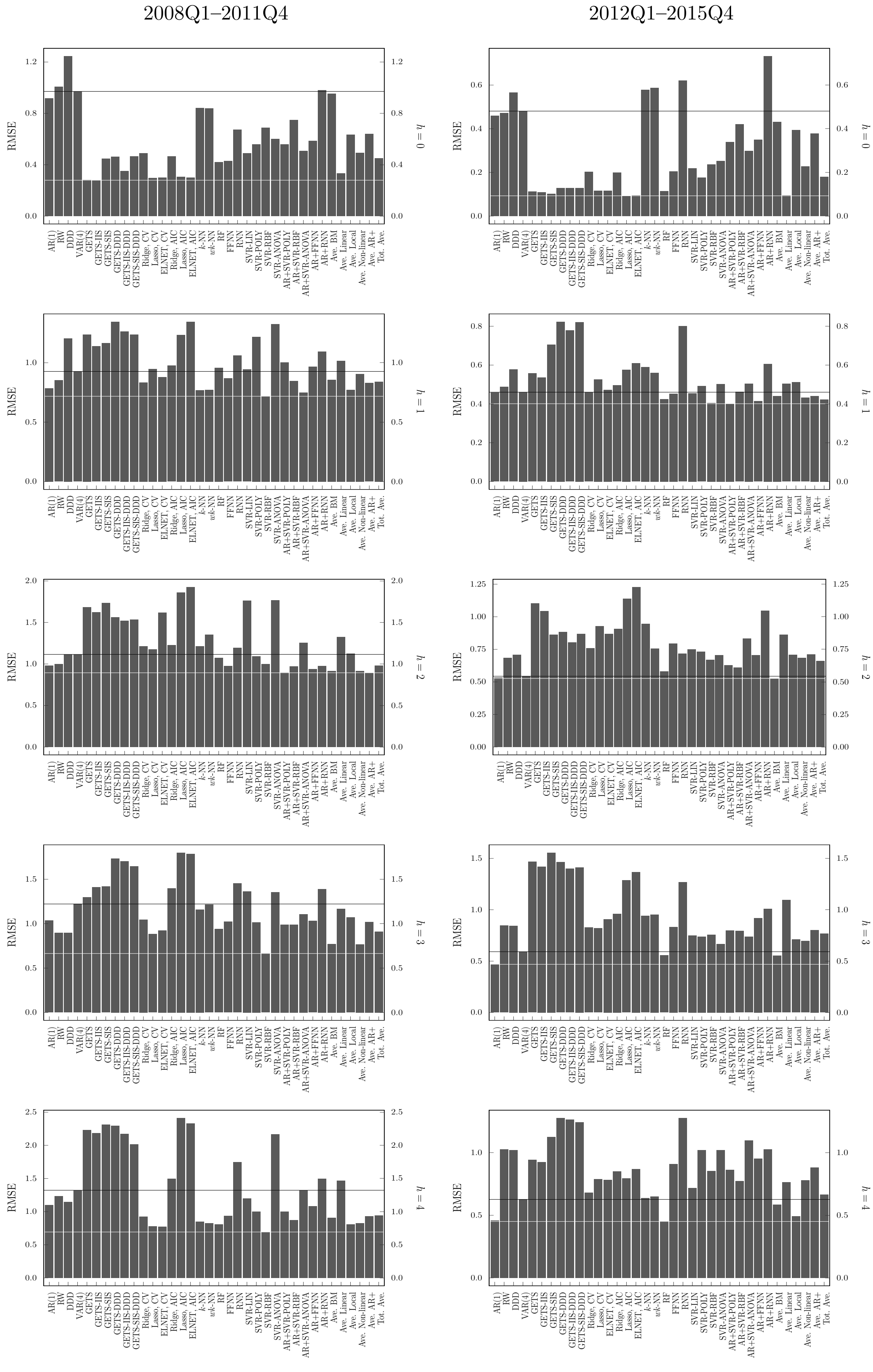

Figure 4.6: RMSE in different parts of the out-sample. Inflation. Multivariate. Horizons from $h = 0$ in the upper panel to $h = 4$ in the lowest. Black line denotes the auto-regressive benchmark, white line the lowest RMSE at each horizon.

5 Discussion

The results presented in the above section indicate that no forecasting model is superior. The optimal model depend both on the target, the horizon and the conditioning variables. Moreover, the model performing best in one particular case might very well perform badly in an other. Interestingly, the average of the benchmark model seems hard to beat also in the case where the forecasts is conditioned on an extensive set of contemporaneous information, at least in forecasing inflation – borrowing the words of Caruana and Niculescu-Mizil (2006), this simple average of the benchmark models is the approach closest to provide a 'free lunch'. For the GDP-growth, the lowest RMSEs are obtained with the SVR models in most cases, and the gain of including contemporaneous information seems to be larger.

Too strong conclusion should, however, not be drawn. First, comparing a large set of models has likely hindered each of them to perform at it's best. Admittedly, the implementation of this exercise have been rather naive, both from a machine learning and from an econometric view, one could say. In a *real* real-time forecasting situation one may wish to be more careful; with respect to the initial variable selection, the modelling and implementation. Even though the lack of assumptions posed on the data generating process is indeed one of the main motivations for using machine learning methods, no algorithm is better than what it is fed with. In particular one should be careful when to pose a non-linear structure on the relationship at hand – if the relationship between y and x is indeed well approximated as a linear one, one should not expect that the more complex approaches outperforms the simple OLS. Teräsvirta et al. (2005) provides an illustration of this issue, finding that auto-regressive forecasts modelled with neural networks only when linearity is rejected perform better than pure non-linear forecast. No tests for linearity is carried through in this exercise.[39]

These authors also carry out a pre-selection of variables (lag length, since they only consider the univariate case). That might have been useful strategy also in this context, in particular for the neural networks which showed rather poor performance in this empirical exercise. The number of parameters that need to be estimated in these models increase rapidly with the number of inputs. When the number of observations is limited, as in this case, these *data-hungry* models might suffer from overfitting. Fitting the models on a larger sample, for example by using using monthly data in forecasting inflation, or choosing an earlier GDP-release as actual, would have been an interesting exercise, which remain for further work.

[39]As pointed out in Teräsvirta (2006), if one reject linearity one should also reject equal predictive accuracy of a non-linear model that nests a linear model. Such an approach may then make MDM-test abundant, which would have been particularly useful in comparing the AR+ and AR models in this exercise. Although, an in-sample test for linearity might be rejected also in the case where it should not be rejected out-of-sample.

Nevertheless, for the comparison of different methods, using them 'out-of-the-box' is also of interest. That said, the machine learning methods applied in this exercise have shown to differ in how much they depend on different tuning parameters. A more detailed search grid might have changed the outcome for some of these methods. Here, due to limited computational power, considering a larger number of tuning parameter has not been feasible. Therefore, the simple approach to use the same set of candidate parameters for each dependent variable and each horizon was undertaken. A feasible alternative would have been to consider a larger set of tuning parameters, but avvoid 'retuning' the model at each origin. That would, of course, neither be optimal since the parameters would in that case not be allowed to depend on time. As a minimum, letting the search grid vary for each target. In particular, for the SVR-models, where the minimum deviation parameter ϵ depend on the scale of the dependent variable, it would be reasonable to either provide distinct or a larger search grid in forecasting the non-linear unit.

Further, only direct forecast are computed. The question of whether to use dynamic or direct strategy for multi-step ahead forecasting is addressed several places. Chevillon and Hendry (2005) compare the two strategies, arguing that the dynamic approach produce more accurate forecasts whenever the data does not inhabit deterministic or stochastic trends.[40] Taieb (2014) finds that using machine learning models with a direct strategy provide better performance only when the time series are long. When that is not the case, such forecasts holds high variance due to overfitting. However, the aforementioned does only consider univariate models. Here, the choice of the direct strategy in order to avoid estimating the evolution of all conditioning variables, which would have been very time consuming if carried through with all the different methods at hand. Of course, one could have modelled these with simpler processes. Or, one could have mixed the two strategies - using what Bontempi et al. (2013) calls the *DIREC* approach: including as additional right-hand side variables estimates of the dependent variable for longer horizons.

Also, the choice of performance might affect which method that produced the best predictions. The models are only compared in terms of (root) mean-squared forecasting error. Other loss function may be of interest in the *real* real-time setting. In this case particularly relevant for the difference devices, who's main advantage is unbiasedness in presence of breaks, at the cost of higher variance. In that regard, it should also be said that both dependent variables are growth rates, ie already differenced once. As well, all included series is differenced until stationarity based on tests evaluated at the complete estimation sample. Significant trend breaks and or shifts in all variables are thereby

[40]Noting that, in terms of the companion form coefficient matrix Φ, the relative forecast accuarcy is a matter of how accurate one are able to estimate the powered estimate Φ^h versus the estimated power Φ_h (p. 204).

removed, which not allow the difference devices to shine.[41] Further, one may argue that comparing point forecast is not the most relevant in a *real* real-time context. Assessing the uncertainty associated with each forecast, either by constructing prediction intervals or experimenting with density forecasts remain undone in this exercise.

Finally, one could have specified better econometric models that ought to be included in this comparison. This holds also for the machine learning models – there exist more sophisticated approaches, such as deep neural networks with 'long time' memory (Lipton, 2015).

6 Conclusion

This thesis has compared the performance of selected machine learning methods to simpler econometric forecasting models in providing short-term forecasts of the four quarter change in Norwegian GDP and CPI. In particular, forecasts obtained with penalized regression, the GETS-algorithm, nearest neighbours, SVR and neural networks have been compared to linear (vector) auto-regressive models, both in the univariate and multivariate context. The SVR approach provide the best overall forecasts of GDP-growth, either when combined with a linear AR model or alone. For most of the horizons these are significantly more accurate than the VAR benchmark. Yet, no single model among the SVR models is the best at all horizon. Also, in forecasting inflation, these methods perform rather bad at some horizons. The random forest produce more accurate forecast compared to the benchmark at the longest horizon, for both targets. The simple linear auto-regressive models seems, nevertheless, hard to beat, particular in forecasting inflation. These methods has also the advantage of being interpretable and easy to compute.

Too strong conclusions should, however, not be drawn. Comparing a large set of models has the disadvantage of not optimizing a single approach. Answering the question of whether machine learning is useful in short-term forecasting of main macroeconomic variables, the answer is, as in Caruana and Niculescu-Mizil (2006) that there is 'no free lunch'. For future work, properly assessing potential non-linearities before estimating such an relationship seems to be the first step in obtaining increased forecasting accuracy. Also, experimenting with different forecast combinations is a natural extension to the work done here.

[41]In the words of Clements and Hendry (2006, p. 634) 'When there are no locations shifts, the "insurance" of differencing must worsen forecast accuracy and precision, but if location shifts occur, differencing will pay.'

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A Annex

A.1 First and 'first final' GDP release

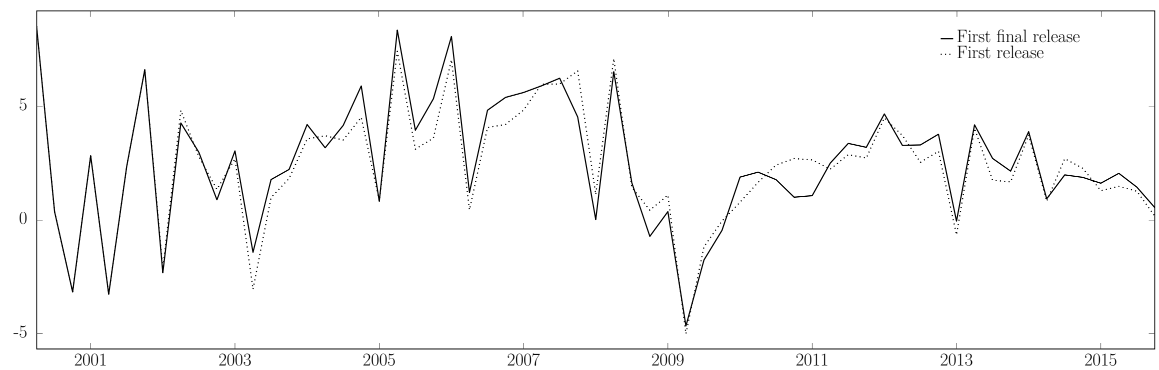

Figure A.1: The first release and the 'first final' release of GDP-growth.

A.2 Comparison of the uni- and multivariate benchmark

Table A.2.1: Benchmark RMSE and modified DM-test. GDP-growth.

	1	2	3	4
AR(p)	1.826	2.409	2.771	3.071
VAR(4)	2.193	2.548	2.655	2.979
Test stat.	-0.609	-1.383	-1.105	-0.548
p-value	(0.547)	(0.177)	(0.278)	(0.588)

Note: This table report RMSE and test statistics for the two-sided modified DM-test of equal forecast accuracy, comparing the uni- and multivariate benchmark. Based on complete out-sample (2008Q1–2015Q4). The loss function used is the DM test is squared errors. *p*-values reported in parentheses.

Table A.2.2: Benchmark RMSE and modified DM-test. Inflation.

	1	2	3	4
AR(p)	0.613	0.793	0.886	0.877
VAR(4)	0.739	0.895	0.990	1.081
Test stat.	-0.632	0.252	0.732	1.544
p-value	(0.532)	(0.803)	(0.470)	(0.134)

Note: This table report RMSE and test statistics for the two-sided modified DM-test of equal forecast accuracy, comparing the uni- and multivariate benchmark. Based on complete out-sample (2008Q1–2015Q4). The loss function used is the DM test is squared errors. *p*-values reported in parentheses.

A.3 Modified DM-test for equal forecast accuracy. Pairwise comparison of each model.

Table A.3.1: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 1$. $N = 31$.

	AR(1)	RW	DDD	AR(p)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	0.013	-0.014	1.417	1.043	0.887	0.976	0.904	0.926	0.945	1.395	1.356
	-	(0.505)	(0.494)	(0.917)	(0.847)	(0.809)	(0.832)	(0.814)	(0.819)	(0.824)	(0.913)	(0.907)
RW	-0.013	-	-0.323	1.366	0.776	0.689	0.800	1.422	1.370	1.470	1.277	1.296
	(0.495)	-	(0.374)	(0.909)	(0.778)	(0.752)	(0.785)	(0.917)	(0.909)	(0.924)	(0.894)	(0.897)
DDD	0.014	0.323	-	1.421	0.813	0.724	0.837	1.479	1.430	1.535	1.331	1.348
	(0.506)	(0.626)	-	(0.917)	(0.789)	(0.763)	(0.795)	(0.925)	(0.918)	(0.932)	(0.903)	(0.906)
AR(p)	-1.417	-1.366	-1.421	-	**-1.715**	**-2.002**	-1.409	-0.244	-0.187	-0.178	-1.418	-1.280
	(0.083)	(0.091)	(0.083)	-	**(0.048)**	**(0.027)**	(0.085)	(0.405)	(0.427)	(0.430)	(0.083)	(0.105)
GETS	-1.043	-0.776	-0.813	1.715	-	-0.485	0.154	0.505	0.552	0.554	1.486	1.502
	(0.153)	(0.222)	(0.211)	(0.952)	-	(0.316)	(0.561)	(0.692)	(0.708)	(0.708)	(0.926)	(0.928)
GETS-IIS	-0.887	-0.689	-0.724	2.002	0.485	-	0.334	0.596	0.653	0.645	1.733	1.794
	(0.191)	(0.248)	(0.237)	(0.973)	(0.684)	-	(0.630)	(0.722)	(0.741)	(0.738)	(0.953)	(0.959)
GETS-SIS	-0.976	-0.800	-0.837	1.409	-0.154	-0.334	-	0.446	0.492	0.499	1.091	1.201
	(0.168)	(0.215)	(0.205)	(0.915)	(0.439)	(0.370)	-	(0.671)	(0.687)	(0.689)	(0.858)	(0.880)
GETS-DDD	-0.904	-1.422	-1.479	0.244	-0.505	-0.596	-0.446	-	0.319	0.584	0.027	0.130
	(0.186)	(0.083)	(0.075)	(0.595)	(0.308)	(0.278)	(0.329)	-	(0.624)	(0.718)	(0.511)	(0.551)
GETS-IIS-DDD	-0.926	-1.370	-1.430	0.187	-0.552	-0.653	-0.492	-0.319	-	0.044	-0.029	0.072
	(0.181)	(0.091)	(0.082)	(0.573)	(0.292)	(0.259)	(0.313)	(0.376)	-	(0.517)	(0.488)	(0.529)
GETS-SIS-DDD	-0.945	-1.470	-1.535	0.178	-0.554	-0.645	-0.499	-0.584	-0.044	-	-0.036	0.064
	(0.176)	(0.076)	(0.068)	(0.570)	(0.292)	(0.262)	(0.311)	(0.282)	(0.483)	-	(0.486)	(0.525)
Ridge, CV	-1.395	-1.277	-1.331	1.418	-1.486	**-1.733**	-1.091	-0.027	0.029	0.036	-	0.828
	(0.087)	(0.106)	(0.097)	(0.917)	(0.074)	**(0.047)**	(0.142)	(0.489)	(0.512)	(0.514)	-	(0.793)
Lasso, CV	-1.356	-1.296	-1.348	1.280	-1.502	**-1.794**	-1.201	-0.130	-0.072	-0.064	-0.828	-
	(0.093)	(0.103)	(0.094)	(0.895)	(0.072)	**(0.041)**	(0.120)	(0.449)	(0.471)	(0.475)	(0.207)	-
ELNET, CV	-1.342	-1.282	-1.335	1.504	-1.455	**-1.740**	-1.164	-0.108	-0.051	-0.043	-0.664	1.118
	(0.095)	(0.105)	(0.096)	(0.929)	(0.078)	**(0.046)**	(0.127)	(0.457)	(0.480)	(0.483)	(0.256)	(0.864)
Ridge, AIC	-1.452	-1.347	-1.403	0.917	**-1.736**	**-1.981**	-1.316	-0.137	-0.081	-0.074	-1.496	-0.082
	(0.078)	(0.094)	(0.085)	(0.817)	**(0.046)**	**(0.028)**	(0.099)	(0.446)	(0.468)	(0.471)	(0.073)	(0.468)
Lasso, AIC	-1.417	-1.361	-1.416	1.320	**-1.715**	**-2.001**	-1.397	-0.231	-0.173	-0.165	-1.407	-1.144
	(0.083)	(0.092)	(0.084)	(0.902)	**(0.048)**	**(0.027)**	(0.086)	(0.410)	(0.432)	(0.435)	(0.085)	(0.131)
ELNET, AIC	-1.418	-1.363	-1.418	1.113	**-1.717**	**-2.002**	-1.400	-0.232	-0.175	-0.166	-1.423	-1.163
	(0.083)	(0.092)	(0.083)	(0.863)	**(0.048)**	**(0.027)**	(0.086)	(0.409)	(0.431)	(0.435)	(0.082)	(0.127)
k-NN	1.307	0.779	0.765	2.880	2.261	2.160	2.132	1.780	1.825	1.836	2.949	2.855
	(0.900)	(0.779)	(0.775)	(0.996)	(0.984)	(0.981)	(0.979)	(0.957)	(0.961)	(0.962)	(0.997)	(0.996)
wk-NN	2.090	0.881	0.865	2.310	2.079	1.983	1.959	1.567	1.600	1.609	2.342	2.273
	(0.977)	(0.807)	(0.803)	(0.986)	(0.977)	(0.972)	(0.970)	(0.936)	(0.940)	(0.941)	(0.987)	(0.985)
RF	**-1.718**	-0.826	-0.876	0.987	0.139	0.023	0.202	0.485	0.515	0.533	0.892	0.894
	(0.048)	(0.208)	(0.194)	(0.834)	(0.555)	(0.509)	(0.579)	(0.684)	(0.695)	(0.701)	(0.810)	(0.811)
FFNN	-1.343	-1.355	-1.410	0.831	-0.735	-0.852	-0.524	0.174	0.219	0.234	0.489	0.628
	(0.095)	(0.093)	(0.084)	(0.794)	(0.234)	(0.201)	(0.302)	(0.568)	(0.586)	(0.592)	(0.686)	(0.733)
RNN	-1.243	-1.230	-1.290	0.764	-0.808	-1.048	-0.651	0.108	0.168	0.175	0.328	0.535
	(0.112)	(0.114)	(0.103)	(0.775)	(0.213)	(0.152)	(0.260)	(0.542)	(0.566)	(0.569)	(0.628)	(0.702)
SVR-LIN	-1.545	-1.445	-1.506	-0.263	**-1.750**	**-2.197**	-1.488	-0.290	-0.240	-0.230	-1.163	-0.689
	(0.066)	(0.079)	(0.071)	(0.397)	**(0.045)**	**(0.018)**	(0.074)	(0.387)	(0.406)	(0.410)	(0.127)	(0.248)
SVR-POLY	-1.402	-1.171	-1.221	0.627	-0.911	-1.073	-0.858	0.069	0.118	0.124	0.246	0.421
	(0.086)	(0.125)	(0.116)	(0.732)	(0.185)	(0.146)	(0.199)	(0.527)	(0.547)	(0.549)	(0.596)	(0.662)
SVR-RBF	-1.197	-1.055	-1.110	0.758	-0.278	-0.390	-0.196	0.306	0.358	0.369	0.551	0.634
	(0.120)	(0.150)	(0.138)	(0.773)	(0.391)	(0.350)	(0.423)	(0.619)	(0.639)	(0.643)	(0.707)	(0.735)
SVR-ANOVA	-1.047	-0.933	-0.977	0.846	-0.411	-0.521	-0.299	0.257	0.312	0.317	0.534	0.686
	(0.152)	(0.179)	(0.168)	(0.798)	(0.342)	(0.303)	(0.384)	(0.601)	(0.621)	(0.623)	(0.701)	(0.751)
AR+SVR-POLY	-1.106	-1.127	-1.173	1.233	-0.814	-1.046	-0.704	0.110	0.175	0.180	0.367	0.802
	(0.139)	(0.134)	(0.125)	(0.886)	(0.211)	(0.152)	(0.243)	(0.544)	(0.569)	(0.571)	(0.642)	(0.786)
AR+SVR-RBF	-0.858	-0.928	-0.967	0.889	-0.345	-0.498	-0.284	0.332	0.411	0.402	0.493	0.702
	(0.199)	(0.180)	(0.171)	(0.809)	(0.366)	(0.311)	(0.389)	(0.629)	(0.658)	(0.655)	(0.687)	(0.756)
AR+SVR-ANOVA	-1.330	-1.310	-1.365	0.454	-1.311	-1.632	-1.224	-0.151	-0.093	-0.084	-0.460	-0.077
	(0.097)	(0.100)	(0.091)	(0.673)	(0.100)	(0.057)	(0.115)	(0.440)	(0.463)	(0.467)	(0.324)	(0.470)
AR+FFNN	-1.372	-1.376	-1.433	-0.114	-1.417	-1.633	-1.346	-0.270	-0.210	-0.203	-0.913	-0.667
	(0.090)	(0.089)	(0.081)	(0.455)	(0.083)	(0.056)	(0.094)	(0.394)	(0.418)	(0.420)	(0.184)	(0.255)
AR+RNN	-0.758	-1.054	-1.144	0.520	-0.169	-0.240	-0.117	0.390	0.452	0.476	0.346	0.426
	(0.227)	(0.150)	(0.131)	(0.696)	(0.433)	(0.406)	(0.454)	(0.650)	(0.673)	(0.681)	(0.634)	(0.664)
Ave. BM	-0.848	-1.557	-1.693	0.863	0.182	0.099	0.243	0.627	0.641	0.678	0.752	0.784
	(0.202)	(0.065)	(0.050)	(0.802)	(0.572)	(0.539)	(0.595)	(0.732)	(0.737)	(0.748)	(0.771)	(0.780)
Ave. Linear	-1.437	-1.550	-1.609	-0.994	**-1.701**	**-1.996**	-1.560	-0.531	-0.467	-0.452	-1.373	-1.345
	(0.081)	(0.066)	(0.059)	(0.164)	**(0.050)**	**(0.028)**	(0.065)	(0.300)	(0.322)	(0.327)	(0.090)	(0.094)
Ave. Local	0.462	0.194	0.169	2.027	1.499	1.340	1.396	1.193	1.224	1.243	2.063	1.973
	(0.676)	(0.576)	(0.566)	(0.974)	(0.928)	(0.905)	(0.914)	(0.879)	(0.885)	(0.888)	(0.976)	(0.971)
Ave. Non-linear	-1.686	-1.530	-1.594	-0.248	-1.609	**-1.844**	-1.365	-0.301	-0.249	-0.244	-1.098	-0.574
	(0.051)	(0.068)	(0.061)	(0.403)	(0.059)	**(0.038)**	(0.091)	(0.383)	(0.402)	(0.404)	(0.140)	(0.285)
Ave. AR+	-1.518	**-1.736**	**-1.809**	-1.060	-1.608	**-1.877**	-1.581	-0.805	-0.749	-0.736	-1.404	-1.302
	(0.070)	**(0.046)**	**(0.040)**	(0.149)	(0.059)	**(0.035)**	(0.062)	(0.214)	(0.230)	(0.234)	(0.085)	(0.101)
Tot. Ave.	-1.577	-1.598	-1.663	-0.728	**-1.766**	**-2.082**	-1.558	-0.422	-0.363	-0.356	**-1.828**	-1.235
	(0.063)	(0.060)	(0.053)	(0.236)	**(0.044)**	**(0.023)**	(0.065)	(0.338)	(0.359)	(0.362)	**(0.039)**	(0.113)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.2: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 1$. $N = 31$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	1.342	1.452	1.417	1.418	-1.307	**-2.090**	1.718	1.343	1.243	1.545	1.402	1.197
	(0.905)	(0.922)	(0.917)	(0.917)	(0.100)	**(0.023)**	(0.952)	(0.905)	(0.888)	(0.934)	(0.914)	(0.880)
RW	1.282	1.347	1.361	1.363	-0.779	-0.881	0.826	1.355	1.230	1.445	1.171	1.055
	(0.895)	(0.906)	(0.908)	(0.908)	(0.221)	(0.193)	(0.792)	(0.907)	(0.886)	(0.921)	(0.875)	(0.850)
DDD	1.335	1.403	1.416	1.418	-0.765	-0.865	0.876	1.410	1.290	1.506	1.221	1.110
	(0.904)	(0.915)	(0.916)	(0.917)	(0.225)	(0.197)	(0.806)	(0.916)	(0.897)	(0.929)	(0.884)	(0.862)
AR(p)	-1.504	-0.917	-1.320	-1.113	**-2.880**	**-2.310**	-0.987	-0.831	-0.764	0.263	-0.627	-0.758
	(0.071)	(0.183)	(0.098)	(0.137)	**(0.004)**	**(0.014)**	(0.166)	(0.206)	(0.225)	(0.603)	(0.268)	(0.227)
GETS	1.455	1.736	1.715	1.717	**-2.261**	**-2.079**	-0.139	0.735	0.808	1.750	0.911	0.278
	(0.922)	(0.954)	(0.952)	(0.952)	**(0.016)**	**(0.023)**	(0.445)	(0.766)	(0.787)	(0.955)	(0.815)	(0.609)
GETS-IIS	1.740	1.981	2.001	2.002	**-2.160**	**-1.983**	-0.023	0.852	1.048	2.197	1.073	0.390
	(0.954)	(0.972)	(0.973)	(0.973)	**(0.019)**	**(0.028)**	(0.491)	(0.799)	(0.848)	(0.982)	(0.854)	(0.650)
GETS-SIS	1.164	1.316	1.397	1.400	**-2.132**	**-1.959**	-0.202	0.524	0.651	1.488	0.858	0.196
	(0.873)	(0.901)	(0.914)	(0.914)	**(0.021)**	**(0.030)**	(0.421)	(0.698)	(0.740)	(0.926)	(0.801)	(0.577)
GETS-DDD	0.108	0.137	0.231	0.232	**-1.780**	-1.567	-0.485	-0.174	-0.108	0.290	-0.069	-0.306
	(0.543)	(0.554)	(0.590)	(0.591)	**(0.043)**	(0.064)	(0.316)	(0.432)	(0.458)	(0.613)	(0.473)	(0.381)
GETS-IIS-DDD	0.051	0.081	0.173	0.175	**-1.825**	-1.600	-0.515	-0.219	-0.168	0.240	-0.118	-0.358
	(0.520)	(0.532)	(0.568)	(0.569)	**(0.039)**	(0.060)	(0.305)	(0.414)	(0.434)	(0.594)	(0.453)	(0.361)
GETS-SIS-DDD	0.043	0.074	0.165	0.166	**-1.836**	-1.609	-0.533	-0.234	-0.175	0.230	-0.124	-0.369
	(0.517)	(0.529)	(0.565)	(0.565)	**(0.038)**	(0.059)	(0.299)	(0.408)	(0.431)	(0.590)	(0.451)	(0.357)
Ridge, CV	0.664	1.496	1.407	1.423	**-2.949**	**-2.342**	-0.892	-0.489	-0.328	1.163	-0.246	-0.551
	(0.744)	(0.927)	(0.915)	(0.918)	**(0.003)**	**(0.013)**	(0.190)	(0.314)	(0.372)	(0.873)	(0.404)	(0.293)
Lasso, CV	-1.118	0.082	1.144	1.163	**-2.855**	**-2.273**	-0.894	-0.628	-0.535	0.689	-0.421	-0.634
	(0.136)	(0.532)	(0.869)	(0.873)	**(0.004)**	**(0.015)**	(0.189)	(0.267)	(0.298)	(0.752)	(0.338)	(0.265)
ELNET, CV	-	0.248	1.370	1.390	**-2.832**	**-2.257**	-0.873	-0.585	-0.486	0.769	-0.378	-0.608
	-	(0.597)	(0.910)	(0.913)	**(0.004)**	**(0.016)**	(0.195)	(0.281)	(0.315)	(0.776)	(0.354)	(0.274)
Ridge, AIC	-0.248	-	0.877	0.898	**-2.967**	**-2.373**	-0.989	-0.722	-0.584	0.711	-0.483	-0.684
	(0.403)	-	(0.806)	(0.812)	**(0.003)**	**(0.012)**	(0.165)	(0.238)	(0.282)	(0.759)	(0.316)	(0.250)
Lasso, AIC	-1.370	-0.877	-	1.037	**-2.883**	**-2.312**	-0.983	-0.816	-0.743	0.315	-0.609	-0.747
	(0.090)	(0.194)	-	(0.846)	**(0.004)**	**(0.014)**	(0.167)	(0.211)	(0.232)	(0.622)	(0.273)	(0.230)
ELNET, AIC	-1.390	-0.898	-1.037	-	**-2.886**	**-2.314**	-0.985	-0.819	-0.746	0.309	-0.613	-0.749
	(0.087)	(0.188)	(0.154)	-	**(0.004)**	**(0.014)**	(0.166)	(0.210)	(0.231)	(0.620)	(0.272)	(0.230)
k-NN	2.832	2.967	2.883	2.886	-	-0.388	2.902	2.758	2.501	3.210	3.172	3.187
	(0.996)	(0.997)	(0.996)	(0.996)	-	(0.351)	(0.997)	(0.995)	(0.991)	(0.998)	(0.998)	(0.998)
wk-NN	2.257	2.373	2.312	2.314	0.388	-	2.657	2.291	2.086	2.574	2.421	2.322
	(0.984)	(0.988)	(0.986)	(0.986)	(0.649)	-	(0.994)	(0.985)	(0.977)	(0.992)	(0.989)	(0.986)
RF	0.873	0.989	0.983	0.985	**-2.902**	**-2.657**	-	0.755	0.717	1.136	0.846	0.546
	(0.805)	(0.835)	(0.833)	(0.834)	**(0.003)**	**(0.006)**	-	(0.772)	(0.761)	(0.868)	(0.798)	(0.705)
FFNN	0.585	0.722	0.816	0.819	**-2.758**	**-2.291**	-0.755	-	0.134	0.990	0.172	-0.265
	(0.719)	(0.762)	(0.789)	(0.790)	**(0.005)**	**(0.015)**	(0.228)	-	(0.553)	(0.835)	(0.568)	(0.396)
RNN	0.486	0.584	0.743	0.746	**-2.501**	**-2.086**	-0.717	-0.134	-	0.866	0.043	-0.367
	(0.685)	(0.718)	(0.768)	(0.769)	**(0.009)**	**(0.023)**	(0.239)	(0.447)	-	(0.803)	(0.517)	(0.358)
SVR-LIN	-0.769	-0.711	-0.315	-0.309	**-3.210**	**-2.574**	-1.136	-0.990	-0.866	-	-0.759	-0.933
	(0.224)	(0.241)	(0.378)	(0.380)	**(0.002)**	**(0.008)**	(0.132)	(0.165)	(0.197)	-	(0.227)	(0.179)
SVR-POLY	0.378	0.483	0.609	0.613	**-3.172**	**-2.421**	-0.846	-0.172	-0.043	0.759	-	-0.527
	(0.646)	(0.684)	(0.727)	(0.728)	**(0.002)**	**(0.011)**	(0.202)	(0.432)	(0.483)	(0.773)	-	(0.301)
SVR-RBF	0.608	0.684	0.747	0.749	**-3.187**	**-2.322**	-0.546	0.265	0.367	0.933	0.527	-
	(0.726)	(0.750)	(0.770)	(0.770)	**(0.002)**	**(0.014)**	(0.295)	(0.604)	(0.642)	(0.821)	(0.699)	-
SVR-ANOVA	0.652	0.706	0.829	0.831	**-2.665**	**-1.921**	-0.474	0.141	0.280	0.819	0.415	-0.121
	(0.740)	(0.757)	(0.793)	(0.794)	**(0.006)**	**(0.032)**	(0.320)	(0.556)	(0.609)	(0.790)	(0.660)	(0.452)
AR+SVR-POLY	0.724	0.721	1.171	1.176	**-2.592**	**-2.055**	-0.596	-0.154	-0.011	1.248	0.036	-0.337
	(0.763)	(0.762)	(0.875)	(0.876)	**(0.007)**	**(0.024)**	(0.278)	(0.439)	(0.496)	(0.889)	(0.514)	(0.369)
AR+SVR-RBF	0.668	0.670	0.863	0.865	**-2.246**	**-1.816**	-0.344	0.151	0.251	1.083	0.271	-0.076
	(0.745)	(0.746)	(0.802)	(0.803)	**(0.016)**	**(0.040)**	(0.366)	(0.560)	(0.598)	(0.856)	(0.606)	(0.470)
AR+SVR-ANOVA	-0.175	-0.026	0.391	0.399	**-2.853**	**-2.263**	-0.876	-0.642	-0.561	0.573	-0.515	-0.695
	(0.431)	(0.490)	(0.651)	(0.654)	**(0.004)**	**(0.016)**	(0.194)	(0.263)	(0.290)	(0.714)	(0.305)	(0.246)
AR+FFNN	-0.781	-0.515	-0.179	-0.171	**-2.839**	**-2.263**	-0.957	-0.856	-0.732	0.156	-0.578	-0.756
	(0.221)	(0.305)	(0.430)	(0.433)	**(0.004)**	**(0.016)**	(0.173)	(0.199)	(0.235)	(0.561)	(0.284)	(0.228)
AR+RNN	0.409	0.440	0.510	0.511	-1.560	-1.420	-0.259	0.177	0.269	0.581	0.249	0.017
	(0.657)	(0.669)	(0.693)	(0.694)	(0.065)	(0.083)	(0.399)	(0.569)	(0.605)	(0.717)	(0.597)	(0.507)
Ave. BM	0.768	0.834	0.857	0.859	-1.622	**-1.736**	0.118	0.725	0.678	0.967	0.685	0.464
	(0.776)	(0.794)	(0.801)	(0.801)	(0.058)	**(0.046)**	(0.547)	(0.763)	(0.748)	(0.829)	(0.751)	(0.677)
Ave. Linear	-1.447	-1.102	-1.029	-1.020	**-2.743**	**-2.260**	-1.071	-1.125	-1.211	-0.406	-0.875	-0.945
	(0.079)	(0.140)	(0.156)	(0.158)	**(0.005)**	**(0.016)**	(0.146)	(0.135)	(0.118)	(0.344)	(0.194)	(0.176)
Ave. Local	1.952	2.109	2.030	2.032	**-2.358**	**-2.317**	2.684	1.984	1.751	2.293	2.170	2.049
	(0.970)	(0.978)	(0.974)	(0.974)	**(0.013)**	**(0.014)**	(0.994)	(0.972)	(0.955)	(0.986)	(0.981)	(0.975)
Ave. Non-linear	-0.636	-0.632	-0.286	-0.282	**-3.467**	**-2.632**	-1.405	-1.211	-1.168	-0.070	-1.162	-1.366
	(0.265)	(0.266)	(0.389)	(0.390)	**(0.001)**	**(0.007)**	(0.085)	(0.118)	(0.126)	(0.472)	(0.127)	(0.091)
Ave. AR+	-1.360	-1.187	-1.082	-1.078	**-2.918**	**-2.366**	-1.229	-1.438	-1.546	-0.908	-1.127	-1.270
	(0.092)	(0.122)	(0.144)	(0.145)	**(0.003)**	**(0.012)**	(0.114)	(0.080)	(0.066)	(0.186)	(0.134)	(0.107)
Tot. Ave.	-1.335	-1.274	-0.792	-0.786	**-3.129**	**-2.490**	-1.242	-1.389	-1.372	-0.436	-1.038	-1.138
	(0.096)	(0.106)	(0.217)	(0.219)	**(0.002)**	**(0.009)**	(0.112)	(0.087)	(0.090)	(0.333)	(0.154)	(0.132)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.3: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 1$. $N = 31$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	1.047	1.106	0.858	1.330	1.372	0.758	0.848	1.437	-0.462	1.686	1.518	1.577
	(0.848)	(0.861)	(0.801)	(0.903)	(0.910)	(0.773)	(0.798)	(0.919)	(0.324)	(0.949)	(0.930)	(0.937)
RW	0.933	1.127	0.928	1.310	1.376	1.054	1.557	1.550	-0.194	1.530	1.736	1.598
	(0.821)	(0.866)	(0.820)	(0.900)	(0.911)	(0.850)	(0.935)	(0.934)	(0.424)	(0.932)	(0.954)	(0.940)
DDD	0.977	1.173	0.967	1.365	1.433	1.144	1.693	1.609	-0.169	1.594	1.809	1.663
	(0.832)	(0.875)	(0.829)	(0.909)	(0.919)	(0.869)	(0.950)	(0.941)	(0.434)	(0.939)	(0.960)	(0.947)
AR(p)	-0.846	-1.233	-0.889	-0.454	0.114	-0.520	-0.863	0.994	**-2.027**	0.248	1.060	0.728
	(0.202)	(0.114)	(0.191)	(0.327)	(0.545)	(0.304)	(0.198)	(0.836)	**(0.026)**	(0.597)	(0.851)	(0.764)
GETS	0.411	0.814	0.345	1.311	1.417	0.169	-0.182	1.701	-1.499	1.609	1.608	1.766
	(0.658)	(0.789)	(0.634)	(0.900)	(0.917)	(0.567)	(0.428)	(0.950)	(0.072)	(0.941)	(0.941)	(0.956)
GETS-IIS	0.521	1.046	0.498	1.632	1.633	0.240	-0.099	1.996	-1.340	1.844	1.877	2.082
	(0.697)	(0.848)	(0.689)	(0.943)	(0.944)	(0.594)	(0.461)	(0.972)	(0.095)	(0.962)	(0.965)	(0.977)
GETS-SIS	0.299	0.704	0.284	1.224	1.346	0.117	-0.243	1.560	-1.396	1.365	1.581	1.558
	(0.616)	(0.757)	(0.611)	(0.885)	(0.906)	(0.546)	(0.405)	(0.935)	(0.086)	(0.909)	(0.938)	(0.935)
GETS-DDD	-0.257	-0.110	-0.332	0.151	0.270	-0.390	-0.627	0.531	-1.193	0.301	0.805	0.422
	(0.399)	(0.456)	(0.371)	(0.560)	(0.606)	(0.350)	(0.268)	(0.700)	(0.121)	(0.617)	(0.786)	(0.662)
GETS-IIS-DDD	-0.312	-0.175	-0.411	0.093	0.210	-0.452	-0.641	0.467	-1.224	0.249	0.749	0.363
	(0.379)	(0.431)	(0.342)	(0.537)	(0.582)	(0.327)	(0.263)	(0.678)	(0.115)	(0.598)	(0.770)	(0.641)
GETS-SIS-DDD	-0.317	-0.180	-0.402	0.084	0.203	-0.476	-0.678	0.452	-1.243	0.244	0.736	0.356
	(0.377)	(0.429)	(0.345)	(0.533)	(0.580)	(0.319)	(0.252)	(0.673)	(0.112)	(0.596)	(0.766)	(0.638)
Ridge, CV	-0.534	-0.367	-0.493	0.460	0.913	-0.346	-0.752	1.373	**-2.063**	1.098	1.404	1.828
	(0.299)	(0.358)	(0.313)	(0.676)	(0.816)	(0.366)	(0.229)	(0.910)	**(0.024)**	(0.860)	(0.915)	(0.961)
Lasso, CV	-0.686	-0.802	-0.702	0.077	0.667	-0.426	-0.784	1.345	**-1.973**	0.574	1.302	1.235
	(0.249)	(0.214)	(0.244)	(0.530)	(0.745)	(0.336)	(0.220)	(0.906)	**(0.029)**	(0.715)	(0.899)	(0.887)
ELNET, CV	-0.652	-0.724	-0.668	0.175	0.781	-0.409	-0.768	1.447	**-1.952**	0.636	1.360	1.335
	(0.260)	(0.237)	(0.255)	(0.569)	(0.779)	(0.343)	(0.224)	(0.921)	**(0.030)**	(0.735)	(0.908)	(0.904)
Ridge, AIC	-0.706	-0.721	-0.670	0.026	0.515	-0.440	-0.834	1.102	**-2.109**	0.632	1.187	1.274
	(0.243)	(0.238)	(0.254)	(0.510)	(0.695)	(0.331)	(0.206)	(0.860)	**(0.022)**	(0.734)	(0.878)	(0.894)
Lasso, AIC	-0.829	-1.171	-0.863	-0.391	0.179	-0.510	-0.857	1.029	**-2.030**	0.286	1.082	0.792
	(0.207)	(0.125)	(0.198)	(0.349)	(0.570)	(0.307)	(0.199)	(0.844)	**(0.026)**	(0.611)	(0.856)	(0.783)
ELNET, AIC	-0.831	-1.176	-0.865	-0.399	0.171	-0.511	-0.859	1.020	**-2.032**	0.282	1.078	0.786
	(0.206)	(0.124)	(0.197)	(0.346)	(0.567)	(0.306)	(0.199)	(0.842)	**(0.026)**	(0.610)	(0.855)	(0.781)
k-NN	2.665	2.592	2.246	2.853	2.839	1.560	1.622	2.743	2.358	3.467	2.918	3.129
	(0.994)	(0.993)	(0.984)	(0.996)	(0.996)	(0.935)	(0.942)	(0.995)	(0.987)	(0.999)	(0.997)	(0.998)
wk-NN	1.921	2.055	1.816	2.263	2.263	1.420	1.736	2.260	2.317	2.632	2.366	2.490
	(0.968)	(0.976)	(0.960)	(0.984)	(0.984)	(0.917)	(0.954)	(0.984)	(0.986)	(0.993)	(0.988)	(0.991)
RF	0.474	0.596	0.344	0.876	0.957	0.259	-0.118	1.071	**-2.684**	1.405	1.229	1.242
	(0.680)	(0.722)	(0.634)	(0.806)	(0.827)	(0.601)	(0.453)	(0.854)	**(0.006)**	(0.915)	(0.886)	(0.888)
FFNN	-0.141	0.154	-0.151	0.642	0.856	-0.177	-0.725	1.125	**-1.984**	1.211	1.438	1.389
	(0.444)	(0.561)	(0.440)	(0.737)	(0.801)	(0.431)	(0.237)	(0.865)	**(0.028)**	(0.882)	(0.920)	(0.913)
RNN	-0.280	0.011	-0.251	0.561	0.732	-0.269	-0.678	1.211	**-1.751**	1.168	1.546	1.372
	(0.391)	(0.504)	(0.402)	(0.710)	(0.765)	(0.395)	(0.252)	(0.882)	**(0.045)**	(0.874)	(0.934)	(0.910)
SVR-LIN	-0.819	-1.248	-1.083	-0.573	-0.156	-0.581	-0.967	0.406	**-2.293**	0.070	0.908	0.436
	(0.210)	(0.111)	(0.144)	(0.286)	(0.439)	(0.283)	(0.171)	(0.656)	**(0.014)**	(0.528)	(0.814)	(0.667)
SVR-POLY	-0.415	-0.036	-0.271	0.515	0.578	-0.249	-0.685	0.875	**-2.170**	1.162	1.127	1.038
	(0.340)	(0.486)	(0.394)	(0.695)	(0.716)	(0.403)	(0.249)	(0.806)	**(0.019)**	(0.873)	(0.866)	(0.846)
SVR-RBF	0.121	0.337	0.076	0.695	0.756	-0.017	-0.464	0.945	**-2.049**	1.366	1.270	1.138
	(0.548)	(0.631)	(0.530)	(0.754)	(0.772)	(0.493)	(0.323)	(0.824)	**(0.025)**	(0.909)	(0.893)	(0.868)
SVR-ANOVA	-	0.291	-0.010	0.715	0.809	-0.079	-0.405	1.023	-1.602	1.145	1.220	1.063
	-	(0.614)	(0.496)	(0.760)	(0.787)	(0.469)	(0.344)	(0.843)	(0.060)	(0.869)	(0.884)	(0.852)
AR+SVR-POLY	-0.291	-	-0.489	1.156	1.355	-0.241	-0.582	1.844	-1.653	0.923	2.214	1.574
	(0.386)	-	(0.314)	(0.872)	(0.907)	(0.406)	(0.282)	(0.962)	(0.054)	(0.818)	(0.983)	(0.937)
AR+SVR-RBF	0.010	0.489	-	0.855	1.043	-0.071	-0.381	1.273	-1.315	0.866	1.866	1.167
	(0.504)	(0.686)	-	(0.800)	(0.847)	(0.472)	(0.353)	(0.894)	(0.099)	(0.803)	(0.964)	(0.874)
AR+SVR-ANOVA	-0.715	-1.156	-0.855	-	0.481	-0.452	-0.809	1.199	**-1.945**	0.532	1.499	1.153
	(0.240)	(0.128)	(0.200)	-	(0.683)	(0.327)	(0.212)	(0.880)	**(0.031)**	(0.701)	(0.928)	(0.871)
AR+FFNN	-0.809	-1.355	-1.043	-0.481	-	-0.540	-0.866	0.733	**-1.972**	0.166	1.074	0.514
	(0.213)	(0.093)	(0.153)	(0.317)	-	(0.296)	(0.197)	(0.765)	**(0.029)**	(0.565)	(0.854)	(0.695)
AR+RNN	0.079	0.241	0.071	0.452	0.540	-	-0.366	0.729	-1.008	0.627	1.022	0.704
	(0.531)	(0.594)	(0.528)	(0.673)	(0.704)	-	(0.358)	(0.764)	(0.161)	(0.732)	(0.843)	(0.757)
Ave. BM	0.405	0.582	0.381	0.809	0.866	0.366	-	1.033	-1.085	1.081	1.221	1.109
	(0.656)	(0.718)	(0.647)	(0.788)	(0.803)	(0.642)	-	(0.845)	(0.143)	(0.856)	(0.884)	(0.862)
Ave. Linear	-1.023	**-1.844**	-1.273	-1.199	-0.733	-0.729	-1.033	-	**-1.979**	-0.253	0.769	-0.182
	(0.157)	**(0.038)**	(0.106)	(0.120)	(0.235)	(0.236)	(0.155)	-	**(0.029)**	(0.401)	(0.776)	(0.428)
Ave. Local	1.602	1.653	1.315	1.945	1.972	1.008	1.085	1.979	-	2.551	2.114	2.280
	(0.940)	(0.946)	(0.901)	(0.969)	(0.971)	(0.839)	(0.857)	(0.971)	-	(0.992)	(0.979)	(0.985)
Ave. Non-linear	-1.145	-0.923	-0.866	-0.532	-0.166	-0.627	-1.081	0.253	**-2.551**	-	0.666	0.292
	(0.131)	(0.182)	(0.197)	(0.299)	(0.435)	(0.268)	(0.144)	(0.599)	**(0.008)**	-	(0.745)	(0.614)
Ave. AR+	-1.220	**-2.214**	**-1.866**	-1.499	-1.074	-1.022	-1.221	-0.769	**-2.114**	-0.666	-	-0.879
	(0.116)	**(0.017)**	**(0.036)**	(0.072)	(0.146)	(0.157)	(0.116)	(0.224)	**(0.021)**	(0.255)	-	(0.193)
Tot. Ave.	-1.063	-1.574	-1.167	-1.153	-0.514	-0.704	-1.109	0.182	**-2.280**	-0.292	0.879	-
	(0.148)	(0.063)	(0.126)	(0.129)	(0.305)	(0.243)	(0.138)	(0.572)	**(0.015)**	(0.386)	(0.807)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.4: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 2$. $N = 30$.

	AR(1)	RW	DDD	AR(p)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.318	-0.619	-0.407	-0.990	-1.157	**-11.055**	-1.298	-1.284	-1.287	-0.489	-0.447
	-	(0.376)	(0.270)	(0.344)	(0.165)	(0.128)	**(0.000)**	(0.102)	(0.105)	(0.104)	(0.314)	(0.329)
RW	0.318	-	**-1.972**	0.038	-0.508	-0.677	-0.918	**-4.132**	**-3.881**	**-4.329**	0.002	0.005
	(0.624)	-	**(0.029)**	(0.515)	(0.308)	(0.252)	(0.183)	**(0.000)**	**(0.000)**	**(0.000)**	(0.501)	(0.502)
DDD	0.619	1.972	-	0.502	-0.082	-0.235	-0.382	-1.077	-1.092	-1.011	0.449	0.476
	(0.730)	(0.971)	-	(0.690)	(0.468)	(0.408)	(0.353)	(0.145)	(0.142)	(0.160)	(0.672)	(0.681)
AR(p)	0.407	-0.038	-0.502	-	**-1.969**	**-2.339**	-1.501	-1.072	-1.060	-1.052	-0.279	-0.212
	(0.656)	(0.485)	(0.310)	-	**(0.029)**	**(0.013)**	(0.072)	(0.146)	(0.149)	(0.151)	(0.391)	(0.417)
GETS	0.990	0.508	0.082	1.969	-	-0.941	-0.507	-0.666	-0.654	-0.645	1.572	1.636
	(0.835)	(0.692)	(0.532)	(0.971)	-	(0.177)	(0.308)	(0.255)	(0.259)	(0.262)	(0.937)	(0.944)
GETS-IIS	1.157	0.677	0.235	2.339	0.941	-	-0.195	-0.561	-0.557	-0.541	1.893	1.998
	(0.872)	(0.748)	(0.592)	(0.987)	(0.823)	-	(0.423)	(0.289)	(0.291)	(0.296)	(0.966)	(0.972)
GETS-SIS	11.055	0.918	0.382	1.501	0.507	0.195	-	-0.462	-0.466	-0.445	1.329	1.263
	(1.000)	(0.817)	(0.647)	(0.928)	(0.692)	(0.577)	-	(0.324)	(0.322)	(0.330)	(0.903)	(0.892)
GETS-DDD	1.298	4.132	1.077	1.072	0.666	0.561	0.462	-	-0.128	0.468	1.033	1.037
	(0.898)	(1.000)	(0.855)	(0.854)	(0.745)	(0.711)	(0.676)	-	(0.450)	(0.678)	(0.845)	(0.846)
GETS-IIS-DDD	1.284	3.881	1.092	1.060	0.654	0.557	0.466	0.128	-	0.339	1.020	1.023
	(0.895)	(1.000)	(0.858)	(0.851)	(0.741)	(0.709)	(0.678)	(0.550)	-	(0.632)	(0.842)	(0.843)
GETS-SIS-DDD	1.287	4.329	1.011	1.052	0.645	0.541	0.445	-0.468	-0.339	-	1.013	1.016
	(0.896)	(1.000)	(0.840)	(0.849)	(0.738)	(0.704)	(0.670)	(0.322)	(0.368)	-	(0.840)	(0.841)
Ridge, CV	0.489	-0.002	-0.449	0.279	-1.572	**-1.893**	-1.329	-1.033	-1.020	-1.013	-	0.032
	(0.686)	(0.499)	(0.328)	(0.609)	(0.063)	**(0.034)**	(0.097)	(0.155)	(0.158)	(0.160)	-	(0.513)
Lasso, CV	0.447	-0.005	-0.476	0.212	-1.636	**-1.998**	-1.263	-1.037	-1.023	-1.016	-0.032	-
	(0.671)	(0.498)	(0.319)	(0.583)	(0.056)	**(0.028)**	(0.108)	(0.154)	(0.157)	(0.159)	(0.487)	-
ELNET, CV	0.496	0.043	-0.430	0.649	-1.530	**-1.909**	-1.253	-1.013	-1.001	-0.993	0.551	1.175
	(0.688)	(0.517)	(0.335)	(0.739)	(0.068)	**(0.033)**	(0.110)	(0.160)	(0.163)	(0.165)	(0.707)	(0.875)
Ridge, AIC	0.396	-0.075	-0.512	-0.528	**-2.020**	**-2.331**	-1.592	-1.088	-1.075	-1.069	-0.596	-0.540
	(0.653)	(0.470)	(0.306)	(0.301)	**(0.026)**	**(0.013)**	(0.061)	(0.143)	(0.146)	(0.147)	(0.278)	(0.297)
Lasso, AIC	0.501	0.008	-0.415	0.368	**-1.938**	**-2.236**	-1.542	-1.032	-1.019	-1.014	0.078	0.119
	(0.690)	(0.503)	(0.341)	(0.642)	**(0.031)**	**(0.017)**	(0.067)	(0.155)	(0.158)	(0.160)	(0.531)	(0.547)
ELNET, AIC	0.471	-0.023	-0.434	0.096	**-2.094**	**-2.289**	-1.473	-1.035	-1.021	-1.015	-0.166	-0.164
	(0.679)	(0.491)	(0.334)	(0.538)	**(0.023)**	**(0.015)**	(0.076)	(0.155)	(0.158)	(0.159)	(0.435)	(0.435)
k-NN	1.838	0.908	0.639	2.475	4.399	1.958	0.910	0.010	-0.001	0.029	2.199	2.441
	(0.962)	(0.814)	(0.736)	(0.990)	(1.000)	(0.970)	(0.815)	(0.504)	(0.499)	(0.511)	(0.982)	(0.990)
wk-NN	3.052	1.174	0.819	1.705	1.181	1.023	0.702	0.116	0.098	0.142	1.774	1.692
	(0.998)	(0.875)	(0.790)	(0.951)	(0.876)	(0.843)	(0.756)	(0.546)	(0.539)	(0.556)	(0.957)	(0.949)
RF	0.487	-0.260	-0.590	-0.354	-1.097	-1.297	-1.136	-1.287	-1.258	-1.275	-0.447	-0.402
	(0.685)	(0.399)	(0.280)	(0.363)	(0.141)	(0.102)	(0.133)	(0.104)	(0.109)	(0.106)	(0.329)	(0.345)
FFNN	1.266	0.325	-0.067	0.619	-0.341	-0.554	-0.630	-0.764	-0.741	-0.744	0.563	0.572
	(0.892)	(0.626)	(0.473)	(0.730)	(0.368)	(0.292)	(0.267)	(0.225)	(0.232)	(0.232)	(0.711)	(0.714)
RNN	2.262	0.829	0.332	1.048	0.336	0.100	-0.053	-0.499	-0.489	-0.478	1.047	1.026
	(0.984)	(0.793)	(0.629)	(0.848)	(0.630)	(0.539)	(0.479)	(0.311)	(0.314)	(0.318)	(0.848)	(0.843)
SVR-LIN	-0.024	-0.512	-0.950	-1.078	-1.520	**-1.930**	**-1.759**	-1.408	-1.412	-1.392	-1.083	-1.117
	(0.490)	(0.306)	(0.175)	(0.145)	(0.070)	**(0.032)**	**(0.045)**	(0.085)	(0.084)	(0.087)	(0.144)	(0.137)
SVR-POLY	0.339	-0.127	-0.644	-0.312	**-1.762**	**-1.951**	-1.633	-1.211	-1.179	-1.189	-0.461	-0.558
	(0.631)	(0.450)	(0.262)	(0.379)	**(0.044)**	**(0.030)**	(0.057)	(0.118)	(0.124)	(0.122)	(0.324)	(0.290)
SVR-RBF	0.954	0.657	0.046	0.828	-0.084	-0.329	-0.404	-1.265	-1.188	-1.244	0.725	0.796
	(0.826)	(0.742)	(0.518)	(0.793)	(0.467)	(0.372)	(0.345)	(0.108)	(0.122)	(0.112)	(0.763)	(0.784)
SVR-ANOVA	1.541	0.285	-0.221	0.901	-0.954	-1.233	-1.030	-0.995	-0.955	-0.972	0.738	0.923
	(0.933)	(0.611)	(0.413)	(0.812)	(0.174)	(0.114)	(0.156)	(0.164)	(0.174)	(0.169)	(0.767)	(0.818)
AR+SVR-POLY	3.228	-0.039	-1.236	-0.032	-0.793	-1.114	-1.326	-1.233	-1.244	-1.219	-0.083	-0.077
	(0.998)	(0.485)	(0.113)	(0.487)	(0.217)	(0.137)	(0.098)	(0.114)	(0.112)	(0.116)	(0.467)	(0.470)
AR+SVR-RBF	0.484	0.089	-0.878	0.352	-0.727	-1.114	-1.220	-1.140	-1.139	-1.122	0.263	0.258
	(0.684)	(0.535)	(0.194)	(0.636)	(0.236)	(0.137)	(0.116)	(0.132)	(0.132)	(0.135)	(0.603)	(0.601)
AR+SVR-ANOVA	0.269	-0.259	-0.905	-0.181	-0.991	-1.382	-1.395	-1.214	-1.219	-1.198	-0.248	-0.237
	(0.605)	(0.399)	(0.186)	(0.429)	(0.165)	(0.089)	(0.087)	(0.117)	(0.116)	(0.120)	(0.403)	(0.407)
AR+FFNN	0.337	-0.040	-0.645	0.023	-0.896	-1.288	-1.436	-1.104	-1.114	-1.090	-0.044	-0.036
	(0.631)	(0.484)	(0.262)	(0.509)	(0.189)	(0.104)	(0.081)	(0.139)	(0.137)	(0.142)	(0.483)	(0.486)
AR+RNN	4.110	0.883	2.379	1.384	0.742	0.633	0.526	-0.051	-0.064	-0.032	1.395	1.351
	(1.000)	(0.808)	(0.988)	(0.912)	(0.768)	(0.734)	(0.699)	(0.480)	(0.475)	(0.487)	(0.913)	(0.906)
Ave. BM	-0.160	-1.057	-1.533	-1.016	-1.273	-1.531	**-1.869**	**-2.447**	**-2.504**	**-2.450**	-0.994	-1.123
	(0.437)	(0.150)	(0.068)	(0.159)	(0.107)	(0.068)	**(0.036)**	**(0.010)**	**(0.009)**	**(0.010)**	(0.164)	(0.135)
Ave. Linear	0.056	**-4.748**	**-2.433**	-0.896	-1.530	**-1.942**	-1.612	-1.511	-1.512	-1.486	-0.982	-0.892
	(0.522)	**(0.000)**	**(0.011)**	(0.189)	(0.068)	**(0.031)**	(0.059)	(0.071)	(0.071)	(0.074)	(0.167)	(0.190)
Ave. Local	1.893	0.501	0.173	0.862	0.197	-0.009	-0.123	-0.590	-0.573	-0.572	0.901	0.842
	(0.966)	(0.690)	(0.568)	(0.802)	(0.577)	(0.497)	(0.452)	(0.280)	(0.285)	(0.286)	(0.813)	(0.797)
Ave. Non-linear	0.451	-0.051	-0.577	-0.023	-1.582	**-1.799**	-1.405	-1.214	-1.179	-1.192	-0.141	-0.154
	(0.672)	(0.480)	(0.284)	(0.491)	(0.062)	**(0.041)**	(0.085)	(0.117)	(0.124)	(0.122)	(0.444)	(0.439)
Ave. AR+	0.029	-0.251	**-2.734**	-0.626	-1.229	-1.620	-1.693	-1.391	-1.410	-1.374	-0.683	-0.638
	(0.511)	(0.402)	**(0.005)**	(0.268)	(0.114)	(0.058)	(0.051)	(0.087)	(0.085)	(0.090)	(0.250)	(0.264)
Tot. Ave.	0.004	-0.746	-1.303	-1.252	**-1.806**	**-2.203**	**-1.817**	-1.469	-1.456	-1.447	-1.359	-1.284
	(0.502)	(0.231)	(0.101)	(0.110)	**(0.041)**	**(0.018)**	**(0.040)**	(0.076)	(0.078)	(0.079)	(0.092)	(0.105)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.5: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 2$. $N = 30$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	-0.496	-0.396	-0.501	-0.471	**-1.838**	**-3.052**	-0.487	-1.266	**-2.262**	0.024	-0.339	-0.954
	(0.312)	(0.347)	(0.310)	(0.321)	**(0.038)**	**(0.002)**	(0.315)	(0.108)	**(0.016)**	(0.510)	(0.369)	(0.174)
RW	-0.043	0.075	-0.008	0.023	-0.908	-1.174	0.260	-0.325	-0.829	0.512	0.127	-0.657
	(0.483)	(0.530)	(0.497)	(0.509)	(0.186)	(0.125)	(0.601)	(0.374)	(0.207)	(0.694)	(0.550)	(0.258)
DDD	0.430	0.512	0.415	0.434	-0.639	-0.819	0.590	0.067	-0.332	0.950	0.644	-0.046
	(0.665)	(0.694)	(0.659)	(0.666)	(0.264)	(0.210)	(0.720)	(0.527)	(0.371)	(0.825)	(0.738)	(0.482)
AR(p)	-0.649	0.528	-0.368	-0.096	**-2.475**	**-1.705**	0.354	-0.619	-1.048	1.078	0.312	-0.828
	(0.261)	(0.699)	(0.358)	(0.462)	**(0.010)**	**(0.049)**	(0.637)	(0.270)	(0.152)	(0.855)	(0.621)	(0.207)
GETS	1.530	2.020	1.938	2.094	**-4.399**	-1.181	1.097	0.341	-0.336	1.520	1.762	0.084
	(0.932)	(0.974)	(0.969)	(0.977)	**(0.000)**	(0.124)	(0.859)	(0.632)	(0.370)	(0.930)	(0.956)	(0.533)
GETS-IIS	1.909	2.331	2.236	2.289	**-1.958**	-1.023	1.297	0.554	-0.100	1.930	1.951	0.329
	(0.967)	(0.987)	(0.983)	(0.985)	**(0.030)**	(0.157)	(0.898)	(0.708)	(0.461)	(0.968)	(0.970)	(0.628)
GETS-SIS	1.253	1.592	1.542	1.473	-0.910	-0.702	1.136	0.630	0.053	1.759	1.633	0.404
	(0.890)	(0.939)	(0.933)	(0.924)	(0.185)	(0.244)	(0.867)	(0.733)	(0.521)	(0.955)	(0.943)	(0.655)
GETS-DDD	1.013	1.088	1.032	1.035	-0.010	-0.116	1.287	0.764	0.499	1.408	1.211	1.265
	(0.840)	(0.857)	(0.845)	(0.845)	(0.496)	(0.454)	(0.896)	(0.775)	(0.689)	(0.915)	(0.882)	(0.892)
GETS-IIS-DDD	1.001	1.075	1.019	1.021	0.001	-0.098	1.258	0.741	0.489	1.412	1.179	1.188
	(0.837)	(0.854)	(0.842)	(0.842)	(0.501)	(0.461)	(0.891)	(0.768)	(0.686)	(0.916)	(0.876)	(0.878)
GETS-SIS-DDD	0.993	1.069	1.014	1.015	-0.029	-0.142	1.275	0.744	0.478	1.392	1.189	1.244
	(0.835)	(0.853)	(0.840)	(0.841)	(0.489)	(0.444)	(0.894)	(0.768)	(0.682)	(0.913)	(0.878)	(0.888)
Ridge, CV	-0.551	0.596	-0.078	0.166	**-2.199**	**-1.774**	0.447	-0.563	-1.047	1.083	0.461	-0.725
	(0.293)	(0.722)	(0.469)	(0.565)	**(0.018)**	**(0.043)**	(0.671)	(0.289)	(0.152)	(0.856)	(0.676)	(0.237)
Lasso, CV	-1.175	0.540	-0.119	0.164	**-2.441**	-1.692	0.402	-0.572	-1.026	1.117	0.558	-0.796
	(0.125)	(0.703)	(0.453)	(0.565)	**(0.010)**	(0.051)	(0.655)	(0.286)	(0.157)	(0.863)	(0.710)	(0.216)
ELNET, CV	-	1.163	0.435	0.644	**-2.318**	-1.652	0.460	-0.506	-0.973	1.275	0.793	-0.719
	-	(0.873)	(0.667)	(0.738)	**(0.014)**	(0.055)	(0.675)	(0.308)	(0.169)	(0.894)	(0.783)	(0.239)
Ridge, AIC	-1.163	-	**-7.705**	-0.735	**-2.352**	**-1.827**	0.335	-0.670	-1.109	0.919	0.122	-0.822
	(0.127)	-	**(0.000)**	(0.234)	**(0.013)**	**(0.039)**	(0.630)	(0.254)	(0.138)	(0.817)	(0.548)	(0.209)
Lasso, AIC	-0.435	7.705	-	0.795	**-2.246**	**-1.790**	0.469	-0.542	-0.984	1.081	0.417	-0.691
	(0.333)	(1.000)	-	(0.783)	**(0.016)**	**(0.042)**	(0.679)	(0.296)	(0.167)	(0.856)	(0.660)	(0.248)
ELNET, AIC	-0.644	0.735	-0.795	-	**-2.456**	**-1.826**	0.419	-0.596	-1.030	0.932	0.285	-0.715
	(0.262)	(0.766)	(0.217)	-	**(0.010)**	**(0.039)**	(0.661)	(0.278)	(0.156)	(0.820)	(0.611)	(0.240)
k-NN	2.318	2.352	2.246	2.456	-	-0.205	1.848	1.861	0.895	1.799	2.254	0.969
	(0.986)	(0.987)	(0.984)	(0.990)	-	(0.419)	(0.963)	(0.964)	(0.811)	(0.959)	(0.984)	(0.830)
wk-NN	1.652	1.827	1.790	1.826	0.205	-	3.082	3.611	1.831	4.449	1.821	1.357
	(0.945)	(0.961)	(0.958)	(0.961)	(0.581)	-	(0.998)	(0.999)	(0.961)	(1.000)	(0.961)	(0.907)
RF	-0.460	-0.335	-0.469	-0.419	**-1.848**	**-3.082**	-	-1.526	**-2.690**	1.200	-0.300	-0.926
	(0.325)	(0.370)	(0.321)	(0.339)	**(0.037)**	**(0.002)**	-	(0.069)	**(0.006)**	(0.880)	(0.383)	(0.181)
FFNN	0.506	0.670	0.542	0.596	**-1.861**	**-3.611**	1.526	-	-1.061	0.789	0.802	-0.114
	(0.692)	(0.746)	(0.704)	(0.722)	**(0.036)**	**(0.001)**	(0.931)	-	(0.149)	(0.782)	(0.785)	(0.455)
RNN	0.973	1.109	0.984	1.030	-0.895	**-1.831**	2.690	1.061	-	1.169	1.251	0.315
	(0.831)	(0.862)	(0.833)	(0.844)	(0.189)	**(0.039)**	(0.994)	(0.851)	-	(0.874)	(0.889)	(0.623)
SVR-LIN	-1.275	-0.919	-1.081	-0.932	**-1.799**	**-4.449**	-1.200	-0.789	-1.169	-	-0.724	-1.426
	(0.106)	(0.183)	(0.144)	(0.180)	**(0.041)**	**(0.000)**	(0.120)	(0.218)	(0.126)	-	(0.238)	(0.082)
SVR-POLY	-0.793	-0.122	-0.417	-0.285	**-2.254**	**-1.821**	0.300	-0.802	-1.251	0.724	-	-1.110
	(0.217)	(0.452)	(0.340)	(0.389)	**(0.016)**	**(0.039)**	(0.617)	(0.215)	(0.111)	(0.762)	-	(0.138)
SVR-RBF	0.719	0.822	0.691	0.715	-0.969	-1.357	0.926	0.114	-0.315	1.426	1.110	-
	(0.761)	(0.791)	(0.752)	(0.760)	(0.170)	(0.093)	(0.819)	(0.545)	(0.377)	(0.918)	(0.862)	-
SVR-ANOVA	0.721	0.897	0.666	0.752	**-2.070**	**-6.496**	1.958	-0.222	-0.748	1.157	1.765	-0.501
	(0.762)	(0.812)	(0.745)	(0.771)	**(0.024)**	**(0.000)**	(0.970)	(0.413)	(0.230)	(0.872)	(0.956)	(0.310)
AR+SVR-POLY	-0.148	0.030	-0.101	-0.046	-1.411	**-4.589**	2.238	-0.456	-0.864	0.879	0.084	-0.942
	(0.442)	(0.512)	(0.460)	(0.482)	(0.084)	**(0.000)**	(0.983)	(0.326)	(0.197)	(0.807)	(0.533)	(0.177)
AR+SVR-RBF	0.176	0.438	0.258	0.291	-1.546	-1.325	0.458	-0.329	-0.805	1.548	0.596	-0.897
	(0.569)	(0.668)	(0.601)	(0.613)	(0.066)	(0.098)	(0.675)	(0.372)	(0.214)	(0.934)	(0.722)	(0.189)
AR+SVR-ANOVA	-0.337	-0.102	-0.264	-0.183	-1.586	**-8.143**	0.206	-0.542	-0.975	1.140	-0.040	-1.107
	(0.369)	(0.460)	(0.397)	(0.428)	(0.062)	**(0.000)**	(0.581)	(0.296)	(0.169)	(0.868)	(0.484)	(0.139)
AR+FFNN	-0.125	0.104	-0.067	0.000	-1.554	-1.391	0.285	-0.477	-0.916	1.027	0.152	-0.728
	(0.451)	(0.541)	(0.474)	(0.500)	(0.066)	(0.087)	(0.611)	(0.319)	(0.184)	(0.844)	(0.560)	(0.236)
AR+RNN	1.319	1.447	1.349	1.348	-0.065	-0.294	3.155	0.934	0.624	1.972	1.446	0.857
	(0.901)	(0.921)	(0.906)	(0.906)	(0.474)	(0.385)	(0.998)	(0.821)	(0.731)	(0.971)	(0.921)	(0.801)
Ave. BM	-1.212	-0.829	-0.840	-0.764	-1.308	**-1.810**	-0.288	-0.860	-1.558	-0.396	-0.897	-1.445
	(0.118)	(0.207)	(0.204)	(0.225)	(0.101)	**(0.040)**	(0.388)	(0.198)	(0.065)	(0.348)	(0.189)	(0.080)
Ave. Linear	-1.052	-0.826	-1.042	-0.820	**-2.026**	**-1.778**	-0.046	-0.886	-1.352	0.667	-0.913	**-2.313**
	(0.151)	(0.208)	(0.153)	(0.210)	**(0.026)**	**(0.043)**	(0.482)	(0.191)	(0.093)	(0.745)	(0.184)	**(0.014)**
Ave. Local	0.792	0.969	0.906	0.953	-1.683	**-2.570**	1.966	1.822	-0.213	2.131	1.005	0.265
	(0.783)	(0.830)	(0.814)	(0.826)	(0.052)	**(0.008)**	(0.971)	(0.961)	(0.416)	(0.979)	(0.838)	(0.603)
Ave. Non-linear	-0.333	0.109	-0.150	-0.051	**-2.059**	**-7.938**	0.430	-0.761	-1.368	0.747	0.530	-0.964
	(0.371)	(0.543)	(0.441)	(0.480)	**(0.024)**	**(0.000)**	(0.665)	(0.226)	(0.091)	(0.769)	(0.700)	(0.171)
Ave. AR+	-0.736	-0.576	-0.710	-0.595	**-1.734**	-1.582	-0.066	-0.823	-1.263	0.179	-0.516	-1.426
	(0.234)	(0.285)	(0.242)	(0.278)	**(0.047)**	(0.062)	(0.474)	(0.209)	(0.108)	(0.570)	(0.305)	(0.082)
Tot. Ave.	-1.487	-1.133	-1.297	-1.069	**-2.117**	**-2.044**	-0.128	-1.042	-1.560	0.082	-1.224	**-1.729**
	(0.074)	(0.133)	(0.102)	(0.147)	**(0.021)**	**(0.025)**	(0.450)	(0.153)	(0.065)	(0.532)	(0.115)	**(0.047)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.6: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 2$. $N = 30$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.541	**-3.228**	-0.484	-0.269	-0.337	**-4.110**	0.160	-0.056	**-1.893**	-0.451	-0.029	-0.004
	(0.067)	**(0.002)**	(0.316)	(0.395)	(0.369)	**(0.000)**	(0.563)	(0.478)	**(0.034)**	(0.328)	(0.489)	(0.498)
RW	-0.285	0.039	-0.089	0.259	0.040	-0.883	1.057	4.748	-0.501	0.051	0.251	0.746
	(0.389)	(0.515)	(0.465)	(0.601)	(0.516)	(0.192)	(0.850)	(1.000)	(0.310)	(0.520)	(0.598)	(0.769)
DDD	0.221	1.236	0.878	0.905	0.645	**-2.379**	1.533	2.433	-0.173	0.577	2.734	1.303
	(0.587)	(0.887)	(0.806)	(0.814)	(0.738)	**(0.012)**	(0.932)	(0.989)	(0.432)	(0.716)	(0.995)	(0.899)
AR(p)	-0.901	0.032	-0.352	0.181	-0.023	-1.384	1.016	0.896	-0.862	0.023	0.626	1.252
	(0.188)	(0.513)	(0.364)	(0.571)	(0.491)	(0.088)	(0.841)	(0.811)	(0.198)	(0.509)	(0.732)	(0.890)
GETS	0.954	0.793	0.727	0.991	0.896	-0.742	1.273	1.530	-0.197	1.582	1.229	1.806
	(0.826)	(0.783)	(0.764)	(0.835)	(0.811)	(0.232)	(0.893)	(0.932)	(0.423)	(0.938)	(0.886)	(0.959)
GETS-IIS	1.233	1.114	1.114	1.382	1.288	-0.633	1.531	1.942	0.009	1.799	1.620	2.203
	(0.886)	(0.863)	(0.863)	(0.911)	(0.896)	(0.266)	(0.932)	(0.969)	(0.503)	(0.959)	(0.942)	(0.982)
GETS-SIS	1.030	1.326	1.220	1.395	1.436	-0.526	1.869	1.612	0.123	1.405	1.693	1.817
	(0.844)	(0.902)	(0.884)	(0.913)	(0.919)	(0.301)	(0.964)	(0.941)	(0.548)	(0.915)	(0.949)	(0.960)
GETS-DDD	0.995	1.233	1.140	1.214	1.104	0.051	2.447	1.511	0.590	1.214	1.391	1.469
	(0.836)	(0.886)	(0.868)	(0.883)	(0.861)	(0.520)	(0.990)	(0.929)	(0.720)	(0.883)	(0.913)	(0.924)
GETS-IIS-DDD	0.955	1.244	1.139	1.219	1.114	0.064	2.504	1.512	0.573	1.179	1.410	1.456
	(0.826)	(0.888)	(0.868)	(0.884)	(0.863)	(0.525)	(0.991)	(0.929)	(0.715)	(0.876)	(0.915)	(0.922)
GETS-SIS-DDD	0.972	1.219	1.122	1.198	1.090	0.032	2.450	1.486	0.572	1.192	1.374	1.447
	(0.831)	(0.884)	(0.865)	(0.880)	(0.858)	(0.513)	(0.990)	(0.926)	(0.714)	(0.878)	(0.910)	(0.921)
Ridge, CV	-0.738	0.083	-0.263	0.248	0.044	-1.395	0.994	0.982	-0.901	0.141	0.683	1.359
	(0.233)	(0.533)	(0.397)	(0.597)	(0.517)	(0.087)	(0.836)	(0.833)	(0.187)	(0.556)	(0.750)	(0.908)
Lasso, CV	-0.923	0.077	-0.258	0.237	0.036	-1.351	1.123	0.892	-0.842	0.154	0.638	1.284
	(0.182)	(0.530)	(0.399)	(0.593)	(0.514)	(0.094)	(0.865)	(0.810)	(0.203)	(0.561)	(0.736)	(0.895)
ELNET, CV	-0.721	0.148	-0.176	0.337	0.125	-1.319	1.212	1.052	-0.792	0.333	0.736	1.487
	(0.238)	(0.558)	(0.431)	(0.631)	(0.549)	(0.099)	(0.882)	(0.849)	(0.217)	(0.629)	(0.766)	(0.926)
Ridge, AIC	-0.897	-0.030	-0.438	0.102	-0.104	-1.447	0.829	0.826	-0.969	-0.109	0.576	1.133
	(0.188)	(0.488)	(0.332)	(0.540)	(0.459)	(0.079)	(0.793)	(0.792)	(0.170)	(0.457)	(0.715)	(0.867)
Lasso, AIC	-0.666	0.101	-0.258	0.264	0.067	-1.349	0.840	1.042	-0.906	0.150	0.710	1.297
	(0.255)	(0.540)	(0.399)	(0.603)	(0.526)	(0.094)	(0.796)	(0.847)	(0.186)	(0.559)	(0.758)	(0.898)
ELNET, AIC	-0.752	0.046	-0.291	0.183	0.000	-1.348	0.764	0.820	-0.953	0.051	0.595	1.069
	(0.229)	(0.518)	(0.387)	(0.572)	(0.500)	(0.094)	(0.775)	(0.790)	(0.174)	(0.520)	(0.722)	(0.853)
k-NN	2.070	1.411	1.546	1.586	1.554	0.065	1.308	2.026	1.683	2.059	1.734	2.117
	(0.976)	(0.916)	(0.934)	(0.938)	(0.934)	(0.526)	(0.899)	(0.974)	(0.948)	(0.976)	(0.953)	(0.979)
wk-NN	6.496	4.589	1.325	8.143	1.391	0.294	1.810	1.778	2.570	7.938	1.582	2.044
	(1.000)	(1.000)	(0.902)	(1.000)	(0.913)	(0.615)	(0.960)	(0.957)	(0.992)	(1.000)	(0.938)	(0.975)
RF	**-1.958**	**-2.238**	-0.458	-0.206	-0.285	**-3.155**	0.288	0.046	**-1.966**	-0.430	0.066	0.128
	(0.030)	**(0.017)**	(0.325)	(0.419)	(0.389)	**(0.002)**	(0.612)	(0.518)	**(0.029)**	(0.335)	(0.526)	(0.550)
FFNN	0.222	0.456	0.329	0.542	0.477	-0.934	0.860	0.886	**-1.822**	0.761	0.823	1.042
	(0.587)	(0.674)	(0.628)	(0.704)	(0.681)	(0.179)	(0.802)	(0.809)	**(0.039)**	(0.774)	(0.791)	(0.847)
RNN	0.748	0.864	0.805	0.975	0.916	-0.624	1.558	1.352	0.213	1.368	1.263	1.560
	(0.770)	(0.803)	(0.786)	(0.831)	(0.816)	(0.269)	(0.935)	(0.907)	(0.584)	(0.909)	(0.892)	(0.935)
SVR-LIN	-1.157	-0.879	-1.548	-1.140	-1.027	**-1.972**	0.396	-0.667	**-2.131**	-0.747	-0.179	-0.082
	(0.128)	(0.193)	(0.066)	(0.132)	(0.156)	**(0.029)**	(0.652)	(0.255)	**(0.021)**	(0.231)	(0.430)	(0.468)
SVR-POLY	**-1.765**	-0.084	-0.596	0.040	-0.152	-1.446	0.897	0.913	-1.005	-0.530	0.516	1.224
	(0.044)	(0.467)	(0.278)	(0.516)	(0.440)	(0.079)	(0.811)	(0.816)	(0.162)	(0.300)	(0.695)	(0.885)
SVR-RBF	0.501	0.942	0.897	1.107	0.728	-0.857	1.445	2.313	-0.265	0.964	1.426	1.729
	(0.690)	(0.823)	(0.811)	(0.861)	(0.764)	(0.199)	(0.920)	(0.986)	(0.397)	(0.829)	(0.918)	(0.953)
SVR-ANOVA	-	0.483	0.298	0.634	0.429	-1.024	1.085	1.492	-0.578	1.292	0.946	1.640
	-	(0.684)	(0.616)	(0.734)	(0.665)	(0.157)	(0.857)	(0.927)	(0.284)	(0.897)	(0.824)	(0.944)
AR+SVR-POLY	-0.483	-	-0.861	0.273	-0.092	-1.643	0.421	0.741	-1.294	-0.024	1.661	0.838
	(0.316)	-	(0.198)	(0.607)	(0.464)	(0.056)	(0.661)	(0.768)	(0.103)	(0.491)	(0.946)	(0.796)
AR+SVR-RBF	-0.298	0.861	-	1.199	0.560	-1.361	0.564	1.661	**-3.951**	0.469	1.921	1.983
	(0.384)	(0.802)	-	(0.880)	(0.710)	(0.092)	(0.711)	(0.946)	**(0.000)**	(0.679)	(0.968)	(0.972)
AR+SVR-ANOVA	-0.634	-0.273	-1.199	-	-0.389	-1.618	0.358	0.878	**-1.912**	-0.171	1.570	1.037
	(0.266)	(0.393)	(0.120)	-	(0.350)	(0.058)	(0.639)	(0.807)	**(0.033)**	(0.433)	(0.936)	(0.846)
AR+FFNN	-0.429	0.092	-0.560	0.389	-	-1.506	0.405	0.915	**-2.414**	0.034	1.530	1.112
	(0.335)	(0.536)	(0.290)	(0.650)	-	(0.071)	(0.656)	(0.816)	**(0.011)**	(0.513)	(0.932)	(0.862)
AR+RNN	1.024	1.643	1.361	1.618	1.506	-	1.317	1.943	0.752	1.488	2.147	2.028
	(0.843)	(0.944)	(0.908)	(0.942)	(0.929)	-	(0.901)	(0.969)	(0.771)	(0.926)	(0.980)	(0.974)
Ave. BM	-1.085	-0.421	-0.564	-0.358	-0.405	-1.317	-	-0.181	-1.041	-0.946	-0.137	-0.143
	(0.143)	(0.339)	(0.289)	(0.361)	(0.344)	(0.099)	-	(0.429)	(0.153)	(0.176)	(0.446)	(0.444)
Ave. Linear	-1.492	-0.741	-1.661	-0.878	-0.915	**-1.943**	0.181	-	-1.019	-1.271	0.079	1.166
	(0.073)	(0.232)	(0.054)	(0.193)	(0.184)	**(0.031)**	(0.571)	-	(0.158)	(0.107)	(0.531)	(0.873)
Ave. Local	0.578	1.294	3.951	1.912	2.414	-0.752	1.041	1.019	-	1.079	2.683	1.260
	(0.716)	(0.897)	(1.000)	(0.967)	(0.989)	(0.229)	(0.847)	(0.842)	-	(0.855)	(0.994)	(0.891)
Ave. Non-linear	-1.292	0.024	-0.469	0.171	-0.034	-1.488	0.946	1.271	-1.079	-	0.677	1.625
	(0.103)	(0.509)	(0.321)	(0.567)	(0.487)	(0.074)	(0.824)	(0.893)	(0.145)	-	(0.748)	(0.943)
Ave. AR+	-0.946	-1.661	**-1.921**	-1.570	-1.530	**-2.147**	0.137	-0.079	**-2.683**	-0.677	-	0.099
	(0.176)	(0.054)	**(0.032)**	(0.064)	(0.068)	**(0.020)**	(0.554)	(0.469)	**(0.006)**	(0.252)	-	(0.539)
Tot. Ave.	-1.640	-0.838	**-1.983**	-1.037	-1.112	**-2.028**	0.143	-1.166	-1.260	-1.625	-0.099	-
	(0.056)	(0.204)	**(0.028)**	(0.154)	(0.138)	**(0.026)**	(0.556)	(0.127)	(0.109)	(0.057)	(0.461)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.7: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 3$. $N = 29$.

	AR(1)	RW	DDD	AR(p)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-1.204	**-1.786**	-1.483	-1.545	**-1.711**	**-1.924**	-1.674	**-1.731**	-1.699	-1.448	-1.432
	-	(0.119)	**(0.042)**	(0.075)	(0.067)	**(0.049)**	**(0.032)**	(0.053)	**(0.047)**	(0.050)	(0.079)	(0.082)
RW	1.204	-	**-2.807**	-0.620	-0.783	-0.836	-1.427	-1.368	-1.412	-1.348	-0.683	-0.735
	(0.881)	-	**(0.004)**	(0.270)	(0.220)	(0.205)	(0.082)	(0.091)	(0.084)	(0.094)	(0.250)	(0.234)
DDD	1.786	2.807	-	0.881	0.154	0.178	-1.052	-1.139	-1.170	-1.077	0.312	0.173
	(0.958)	(0.996)	-	(0.807)	(0.561)	(0.570)	(0.151)	(0.132)	(0.126)	(0.145)	(0.621)	(0.568)
AR(p)	1.483	0.620	-0.881	-	-0.819	-1.217	-1.518	**-1.985**	**-2.198**	**-1.892**	-0.366	-0.562
	(0.925)	(0.730)	(0.193)	-	(0.210)	(0.117)	(0.070)	**(0.029)**	**(0.018)**	**(0.034)**	(0.359)	(0.289)
GETS	1.545	0.783	-0.154	0.819	-	0.096	-1.350	-1.525	-1.627	-1.314	0.578	0.041
	(0.933)	(0.780)	(0.439)	(0.790)	-	(0.538)	(0.094)	(0.069)	(0.058)	(0.100)	(0.716)	(0.516)
GETS-IIS	1.711	0.836	-0.178	1.217	-0.096	-	-1.340	-1.429	-1.515	-1.251	0.593	-0.020
	(0.951)	(0.795)	(0.430)	(0.883)	(0.462)	-	(0.095)	(0.082)	(0.070)	(0.111)	(0.721)	(0.492)
GETS-SIS	1.924	1.427	1.052	1.518	1.350	1.340	-	-0.024	-0.031	0.217	1.213	1.165
	(0.968)	(0.918)	(0.849)	(0.930)	(0.906)	(0.905)	-	(0.491)	(0.488)	(0.585)	(0.882)	(0.873)
GETS-DDD	1.674	1.368	1.139	1.985	1.525	1.429	0.024	-	-0.323	1.470	1.621	1.654
	(0.947)	(0.909)	(0.868)	(0.971)	(0.931)	(0.918)	(0.509)	-	(0.375)	(0.924)	(0.942)	(0.945)
GETS-IIS-DDD	1.731	1.412	1.170	2.198	1.627	1.515	0.031	0.323	-	3.407	1.732	1.777
	(0.953)	(0.916)	(0.874)	(0.982)	(0.942)	(0.930)	(0.512)	(0.625)	-	(0.999)	(0.953)	(0.957)
GETS-SIS-DDD	1.699	1.348	1.077	1.892	1.314	1.251	-0.217	-1.470	**-3.407**	-	1.415	1.412
	(0.950)	(0.906)	(0.855)	(0.966)	(0.900)	(0.889)	(0.415)	(0.076)	**(0.001)**	-	(0.916)	(0.916)
Ridge, CV	1.448	0.683	-0.312	0.366	-0.578	-0.593	-1.213	-1.621	**-1.732**	-1.415	-	-1.006
	(0.921)	(0.750)	(0.379)	(0.641)	(0.284)	(0.279)	(0.118)	(0.058)	**(0.047)**	(0.084)	-	(0.161)
Lasso, CV	1.432	0.735	-0.173	0.562	-0.041	0.020	-1.165	-1.654	**-1.777**	-1.412	1.006	-
	(0.918)	(0.766)	(0.432)	(0.711)	(0.484)	(0.508)	(0.127)	(0.055)	**(0.043)**	(0.084)	(0.839)	-
ELNET, CV	1.427	0.729	-0.173	0.553	-0.050	0.011	-1.165	-1.656	**-1.778**	-1.412	0.942	-0.286
	(0.918)	(0.764)	(0.432)	(0.708)	(0.480)	(0.504)	(0.127)	(0.054)	**(0.043)**	(0.084)	(0.823)	(0.388)
Ridge, AIC	1.487	0.721	-0.181	0.758	-0.128	-0.061	-1.382	-1.599	**-1.716**	-1.411	0.242	-0.075
	(0.926)	(0.761)	(0.429)	(0.773)	(0.449)	(0.476)	(0.089)	(0.061)	**(0.049)**	(0.085)	(0.595)	(0.470)
Lasso, AIC	1.503	0.804	-0.505	0.469	-0.213	-0.144	-1.401	-1.579	-1.695	-1.393	0.113	-0.147
	(0.928)	(0.786)	(0.309)	(0.679)	(0.417)	(0.443)	(0.086)	(0.063)	(0.051)	(0.087)	(0.545)	(0.442)
ELNET, AIC	1.504	0.804	0.008	1.063	0.524	1.015	-1.299	-1.555	-1.673	-1.332	0.685	0.401
	(0.928)	(0.786)	(0.503)	(0.852)	(0.698)	(0.841)	(0.102)	(0.066)	(0.053)	(0.097)	(0.751)	(0.654)
k-NN	1.337	0.574	0.007	0.470	0.153	0.176	-1.044	-1.333	-1.404	-1.126	0.290	0.167
	(0.904)	(0.715)	(0.503)	(0.679)	(0.560)	(0.569)	(0.153)	(0.097)	(0.086)	(0.135)	(0.613)	(0.566)
wk-NN	1.125	0.159	-0.714	-0.881	-0.774	-0.783	-1.630	-1.677	**-1.764**	-1.569	-1.515	-1.511
	(0.865)	(0.563)	(0.240)	(0.193)	(0.223)	(0.220)	(0.057)	(0.052)	**(0.044)**	(0.064)	(0.070)	(0.071)
RF	1.293	0.274	-0.459	-0.410	**-3.454**	-0.438	-1.370	-1.422	-1.484	-1.313	-0.878	-0.929
	(0.897)	(0.607)	(0.325)	(0.343)	**(0.001)**	(0.332)	(0.091)	(0.083)	(0.074)	(0.100)	(0.194)	(0.180)
FFNN	2.025	3.743	0.129	0.911	0.637	0.733	-1.020	-1.072	-1.143	-0.880	0.733	0.578
	(0.974)	(1.000)	(0.551)	(0.815)	(0.735)	(0.765)	(0.158)	(0.146)	(0.131)	(0.193)	(0.765)	(0.716)
RNN	1.633	1.090	0.758	1.518	1.646	1.601	0.047	0.024	0.018	0.217	1.536	1.514
	(0.943)	(0.858)	(0.773)	(0.930)	(0.945)	(0.940)	(0.519)	(0.509)	(0.507)	(0.585)	(0.932)	(0.929)
SVR-LIN	1.513	0.923	-0.009	0.529	0.276	0.311	-1.184	-1.227	-1.286	-1.043	0.419	0.221
	(0.929)	(0.818)	(0.497)	(0.699)	(0.608)	(0.621)	(0.123)	(0.115)	(0.104)	(0.153)	(0.661)	(0.587)
SVR-POLY	1.703	1.312	0.986	1.231	1.134	1.147	0.551	0.372	0.373	0.506	1.139	1.110
	(0.950)	(0.900)	(0.834)	(0.886)	(0.867)	(0.869)	(0.707)	(0.644)	(0.644)	(0.692)	(0.868)	(0.862)
SVR-RBF	1.531	0.897	0.418	1.093	1.127	1.008	-0.660	-0.795	-0.819	-0.551	1.388	1.288
	(0.931)	(0.811)	(0.660)	(0.858)	(0.865)	(0.839)	(0.257)	(0.217)	(0.210)	(0.293)	(0.912)	(0.896)
SVR-ANOVA	1.592	1.042	0.508	1.405	1.435	1.164	-0.785	-1.048	-1.100	-0.732	2.468	2.669
	(0.939)	(0.847)	(0.692)	(0.914)	(0.919)	(0.873)	(0.219)	(0.152)	(0.140)	(0.235)	(0.990)	(0.994)
AR+SVR-POLY	1.590	0.290	-0.461	-0.271	-0.428	-0.453	**-2.009**	-1.168	-1.216	-1.125	-0.314	-0.364
	(0.938)	(0.613)	(0.324)	(0.394)	(0.336)	(0.327)	**(0.027)**	(0.126)	(0.117)	(0.135)	(0.378)	(0.359)
AR+SVR-RBF	1.618	0.286	-0.459	-0.267	-0.427	-0.448	**-2.113**	-1.170	-1.219	-1.129	-0.308	-0.357
	(0.942)	(0.611)	(0.325)	(0.396)	(0.336)	(0.329)	**(0.022)**	(0.126)	(0.117)	(0.134)	(0.380)	(0.362)
AR+SVR-ANOVA	1.721	0.107	-0.677	-0.554	-0.707	-0.765	**-2.008**	-1.250	-1.297	-1.209	-0.560	-0.601
	(0.952)	(0.542)	(0.252)	(0.292)	(0.243)	(0.225)	**(0.027)**	(0.111)	(0.103)	(0.118)	(0.290)	(0.276)
AR+FFNN	1.767	0.490	-0.257	-0.016	-0.286	-0.301	**-2.127**	-1.212	-1.269	-1.159	-0.144	-0.218
	(0.956)	(0.686)	(0.400)	(0.494)	(0.389)	(0.383)	**(0.021)**	(0.118)	(0.107)	(0.128)	(0.443)	(0.415)
AR+RNN	2.181	1.655	1.250	1.229	1.103	1.122	0.511	0.387	0.391	0.540	1.091	1.052
	(0.981)	(0.945)	(0.889)	(0.885)	(0.860)	(0.864)	(0.693)	(0.649)	(0.651)	(0.703)	(0.858)	(0.849)
Ave. BM	1.024	-1.403	**-2.076**	-1.260	-1.280	-1.396	**-1.761**	-1.582	-1.633	-1.609	-1.198	-1.211
	(0.843)	(0.086)	**(0.024)**	(0.109)	(0.105)	(0.087)	**(0.045)**	(0.062)	(0.057)	(0.059)	(0.120)	(0.118)
Ave. Linear	1.276	0.174	-1.532	**-1.869**	-1.068	-1.123	**-1.779**	**-2.280**	**-2.499**	**-2.296**	-0.988	-1.063
	(0.894)	(0.569)	(0.068)	**(0.036)**	(0.147)	(0.136)	**(0.043)**	**(0.015)**	**(0.009)**	**(0.015)**	(0.166)	(0.149)
Ave. Local	1.074	0.165	-0.591	-0.771	**-2.992**	-0.760	-1.532	-1.683	**-1.767**	-1.558	-1.357	-1.419
	(0.854)	(0.565)	(0.279)	(0.224)	**(0.003)**	(0.227)	(0.068)	(0.052)	**(0.044)**	(0.065)	(0.093)	(0.084)
Ave. Non-linear	1.479	0.839	0.162	0.751	0.740	0.626	-1.016	-1.151	-1.199	-0.916	1.016	0.775
	(0.925)	(0.796)	(0.564)	(0.770)	(0.767)	(0.732)	(0.159)	(0.130)	(0.120)	(0.184)	(0.841)	(0.778)
Ave. AR+	1.312	0.132	-0.580	-0.420	-0.548	-0.577	**-2.246**	-1.280	-1.336	-1.260	-0.419	-0.464
	(0.900)	(0.552)	(0.283)	(0.339)	(0.294)	(0.284)	**(0.016)**	(0.105)	(0.096)	(0.109)	(0.339)	(0.323)
Tot. Ave.	1.263	0.064	-1.413	**-2.862**	-1.692	**-2.010**	**-1.899**	**-1.980**	**-2.113**	**-1.955**	-1.397	-1.413
	(0.892)	(0.525)	(0.084)	**(0.004)**	(0.051)	**(0.027)**	**(0.034)**	**(0.029)**	**(0.022)**	**(0.030)**	(0.087)	(0.084)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.8: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 3$. $N = 29$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	-1.427	-1.487	-1.503	-1.504	-1.337	-1.125	-1.293	**-2.025**	-1.633	-1.513	**-1.703**	-1.531
	(0.082)	(0.074)	(0.072)	(0.072)	(0.096)	(0.135)	(0.103)	**(0.026)**	(0.057)	(0.071)	**(0.050)**	(0.069)
RW	-0.729	-0.721	-0.804	-0.804	-0.574	-0.159	-0.274	**-3.743**	-1.090	-0.923	-1.312	-0.897
	(0.236)	(0.239)	(0.214)	(0.214)	(0.285)	(0.437)	(0.393)	**(0.000)**	(0.142)	(0.182)	(0.100)	(0.189)
DDD	0.173	0.181	0.505	-0.008	-0.007	0.714	0.459	-0.129	-0.758	0.009	-0.986	-0.418
	(0.568)	(0.571)	(0.691)	(0.497)	(0.497)	(0.760)	(0.675)	(0.449)	(0.227)	(0.503)	(0.166)	(0.340)
AR(p)	-0.553	-0.758	-0.469	-1.063	-0.470	0.881	0.410	-0.911	-1.518	-0.529	-1.231	-1.093
	(0.292)	(0.227)	(0.321)	(0.148)	(0.321)	(0.807)	(0.657)	(0.185)	(0.070)	(0.301)	(0.114)	(0.142)
GETS	0.050	0.128	0.213	-0.524	-0.153	0.774	3.454	-0.637	-1.646	-0.276	-1.134	-1.127
	(0.520)	(0.551)	(0.583)	(0.302)	(0.440)	(0.777)	(0.999)	(0.265)	(0.055)	(0.392)	(0.133)	(0.135)
GETS-IIS	-0.011	0.061	0.144	-1.015	-0.176	0.783	0.438	-0.733	-1.601	-0.311	-1.147	-1.008
	(0.496)	(0.524)	(0.557)	(0.159)	(0.431)	(0.780)	(0.668)	(0.235)	(0.060)	(0.379)	(0.131)	(0.161)
GETS-SIS	1.165	1.382	1.401	1.299	1.044	1.630	1.370	1.020	-0.047	1.184	-0.551	0.660
	(0.873)	(0.911)	(0.914)	(0.898)	(0.847)	(0.943)	(0.909)	(0.842)	(0.481)	(0.877)	(0.293)	(0.743)
GETS-DDD	1.656	1.599	1.579	1.555	1.333	1.677	1.422	1.072	-0.024	1.227	-0.372	0.795
	(0.946)	(0.939)	(0.937)	(0.934)	(0.903)	(0.948)	(0.917)	(0.854)	(0.491)	(0.885)	(0.356)	(0.783)
GETS-IIS-DDD	1.778	1.716	1.695	1.673	1.404	1.764	1.484	1.143	-0.018	1.286	-0.373	0.819
	(0.957)	(0.951)	(0.949)	(0.947)	(0.914)	(0.956)	(0.926)	(0.869)	(0.493)	(0.896)	(0.356)	(0.790)
GETS-SIS-DDD	1.412	1.411	1.393	1.332	1.126	1.569	1.313	0.880	-0.217	1.043	-0.506	0.551
	(0.916)	(0.915)	(0.913)	(0.903)	(0.865)	(0.936)	(0.900)	(0.807)	(0.415)	(0.847)	(0.308)	(0.707)
Ridge, CV	-0.942	-0.242	-0.113	-0.685	-0.290	1.515	0.878	-0.733	-1.536	-0.419	-1.139	-1.388
	(0.177)	(0.405)	(0.455)	(0.249)	(0.387)	(0.930)	(0.806)	(0.235)	(0.068)	(0.339)	(0.132)	(0.088)
Lasso, CV	0.286	0.075	0.147	-0.401	-0.167	1.511	0.929	-0.578	-1.514	-0.221	-1.110	-1.288
	(0.612)	(0.530)	(0.558)	(0.346)	(0.434)	(0.929)	(0.820)	(0.284)	(0.071)	(0.413)	(0.138)	(0.104)
ELNET, CV	-	0.067	0.139	-0.406	-0.170	1.504	0.925	-0.576	-1.517	-0.223	-1.108	-1.305
	-	(0.526)	(0.555)	(0.344)	(0.433)	(0.928)	(0.819)	(0.284)	(0.070)	(0.412)	(0.139)	(0.101)
Ridge, AIC	-0.067	-	0.187	**-1.911**	-0.180	1.671	0.898	-0.689	-1.503	-0.280	-1.158	-1.125
	(0.474)	-	(0.574)	**(0.033)**	(0.429)	(0.947)	(0.812)	(0.248)	(0.072)	(0.391)	(0.128)	(0.135)
Lasso, AIC	-0.139	-0.187	-	-0.923	-0.188	1.363	0.771	-0.932	-1.443	-0.582	-1.196	-1.098
	(0.445)	(0.426)	-	(0.182)	(0.426)	(0.908)	(0.776)	(0.180)	(0.080)	(0.283)	(0.121)	(0.141)
ELNET, AIC	0.406	1.911	0.923	-	-0.007	1.861	1.093	-0.455	-1.465	0.025	-1.113	-0.957
	(0.656)	(0.967)	(0.818)	-	(0.497)	(0.963)	(0.858)	(0.326)	(0.077)	(0.510)	(0.138)	(0.173)
k-NN	0.170	0.180	0.188	0.007	-	1.284	0.756	-0.247	**-1.904**	0.015	-1.020	-0.727
	(0.567)	(0.571)	(0.574)	(0.503)	-	(0.895)	(0.772)	(0.403)	**(0.034)**	(0.506)	(0.158)	(0.237)
wk-NN	-1.504	-1.671	-1.363	**-1.861**	-1.284	-	-0.561	-1.437	**-2.013**	-1.215	-1.326	**-2.550**
	(0.072)	(0.053)	(0.092)	**(0.037)**	(0.105)	-	(0.290)	(0.081)	**(0.027)**	(0.117)	(0.098)	**(0.008)**
RF	-0.925	-0.898	-0.771	-1.093	-0.756	0.561	-	-1.092	-1.685	-0.798	-1.237	**-2.933**
	(0.181)	(0.188)	(0.224)	(0.142)	(0.228)	(0.710)	-	(0.142)	(0.052)	(0.216)	(0.113)	**(0.003)**
FFNN	0.576	0.689	0.932	0.455	0.247	1.437	1.092	-	-1.008	1.089	-1.162	-0.292
	(0.716)	(0.752)	(0.820)	(0.674)	(0.597)	(0.919)	(0.858)	-	(0.161)	(0.857)	(0.128)	(0.386)
RNN	1.517	1.503	1.443	1.465	1.904	2.013	1.685	1.008	-	1.272	-0.472	1.293
	(0.930)	(0.928)	(0.920)	(0.923)	(0.966)	(0.973)	(0.948)	(0.839)	-	(0.893)	(0.320)	(0.897)
SVR-LIN	0.223	0.280	0.582	-0.025	-0.015	1.215	0.798	-1.089	-1.272	-	-1.165	-0.790
	(0.588)	(0.609)	(0.717)	(0.490)	(0.494)	(0.883)	(0.784)	(0.143)	(0.107)	-	(0.127)	(0.218)
SVR-POLY	1.108	1.158	1.196	1.113	1.020	1.326	1.237	1.162	0.472	1.165	-	0.789
	(0.861)	(0.872)	(0.879)	(0.862)	(0.842)	(0.902)	(0.887)	(0.872)	(0.680)	(0.873)	-	(0.782)
SVR-RBF	1.305	1.125	1.098	0.957	0.727	2.550	2.933	0.292	-1.293	0.790	-0.789	-
	(0.899)	(0.865)	(0.859)	(0.827)	(0.763)	(0.992)	(0.997)	(0.614)	(0.103)	(0.782)	(0.218)	-
SVR-ANOVA	2.751	1.662	1.492	1.452	1.174	5.800	3.051	0.286	**-1.823**	1.033	-0.871	-0.156
	(0.995)	(0.946)	(0.927)	(0.921)	(0.875)	(1.000)	(0.998)	(0.612)	**(0.040)**	(0.845)	(0.196)	(0.439)
AR+SVR-POLY	-0.361	-0.406	-0.399	-0.491	-0.384	0.109	-0.036	-0.924	-1.120	-0.479	**-1.819**	-0.655
	(0.360)	(0.344)	(0.346)	(0.314)	(0.352)	(0.543)	(0.486)	(0.182)	(0.136)	(0.318)	**(0.040)**	(0.259)
AR+SVR-RBF	-0.354	-0.404	-0.396	-0.488	-0.376	0.111	-0.035	-0.861	-1.095	-0.465	-1.642	-0.656
	(0.363)	(0.345)	(0.348)	(0.315)	(0.355)	(0.544)	(0.486)	(0.198)	(0.141)	(0.323)	(0.056)	(0.258)
AR+SVR-ANOVA	-0.597	-0.685	-0.708	-0.762	-0.569	-0.088	-0.260	-1.458	-1.299	-0.779	**-1.794**	-0.857
	(0.278)	(0.249)	(0.242)	(0.226)	(0.287)	(0.465)	(0.399)	(0.078)	(0.102)	(0.221)	**(0.042)**	(0.199)
AR+FFNN	-0.215	-0.252	-0.225	-0.382	-0.271	0.444	0.227	-0.798	-1.162	-0.321	-1.534	-0.620
	(0.416)	(0.401)	(0.412)	(0.353)	(0.394)	(0.670)	(0.589)	(0.216)	(0.128)	(0.375)	(0.068)	(0.270)
AR+RNN	1.052	1.119	1.133	1.062	0.983	1.324	1.194	0.984	0.310	1.045	-0.015	0.745
	(0.849)	(0.864)	(0.867)	(0.851)	(0.833)	(0.902)	(0.879)	(0.833)	(0.620)	(0.848)	(0.494)	(0.769)
Ave. BM	-1.205	-1.236	-1.328	-1.276	-0.981	-0.696	-0.802	**-2.512**	-1.338	-1.347	-1.510	-1.227
	(0.119)	(0.113)	(0.098)	(0.106)	(0.167)	(0.246)	(0.215)	**(0.009)**	(0.096)	(0.094)	(0.071)	(0.115)
Ave. Linear	-1.058	-1.243	-1.010	-1.319	-1.000	-0.055	-0.379	-1.130	-1.639	-0.875	-1.269	-1.246
	(0.150)	(0.112)	(0.160)	(0.099)	(0.163)	(0.478)	(0.354)	(0.134)	(0.056)	(0.194)	(0.107)	(0.112)
Ave. Local	-1.417	-1.340	-1.046	-1.558	-1.580	0.184	-0.438	-1.176	**-2.083**	-0.964	-1.274	**-2.727**
	(0.084)	(0.096)	(0.152)	(0.065)	(0.063)	(0.572)	(0.332)	(0.125)	**(0.023)**	(0.172)	(0.107)	**(0.005)**
Ave. Non-linear	0.785	0.704	0.831	0.396	0.194	3.117	2.086	-0.183	-1.550	0.413	-1.007	-1.056
	(0.781)	(0.757)	(0.794)	(0.652)	(0.576)	(0.998)	(0.977)	(0.428)	(0.066)	(0.659)	(0.161)	(0.150)
Ave. AR+	-0.461	-0.527	-0.518	-0.604	-0.474	-0.027	-0.155	-0.956	-1.137	-0.564	-1.657	-0.729
	(0.324)	(0.301)	(0.304)	(0.275)	(0.320)	(0.489)	(0.439)	(0.174)	(0.133)	(0.289)	(0.054)	(0.236)
Tot. Ave.	-1.403	**-1.849**	-1.582	**-1.819**	-1.115	-0.354	-0.722	-1.578	**-1.726**	-1.230	-1.372	-1.470
	(0.086)	**(0.037)**	(0.062)	**(0.040)**	(0.137)	(0.363)	(0.238)	(0.063)	**(0.048)**	(0.114)	(0.090)	(0.076)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.9: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 3$. $N = 29$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.592	-1.590	-1.618	**-1.721**	**-1.767**	**-2.181**	-1.024	-1.276	-1.074	-1.479	-1.312	-1.263
	(0.061)	(0.062)	(0.058)	**(0.048)**	**(0.044)**	**(0.019)**	(0.157)	(0.106)	(0.146)	(0.075)	(0.100)	(0.108)
RW	-1.042	-0.290	-0.286	-0.107	-0.490	-1.655	1.403	-0.174	-0.165	-0.839	-0.132	-0.064
	(0.153)	(0.387)	(0.389)	(0.458)	(0.314)	(0.055)	(0.914)	(0.431)	(0.435)	(0.204)	(0.448)	(0.475)
DDD	-0.508	0.461	0.459	0.677	0.257	-1.250	2.076	1.532	0.591	-0.162	0.580	1.413
	(0.308)	(0.676)	(0.675)	(0.748)	(0.600)	(0.111)	(0.976)	(0.932)	(0.721)	(0.436)	(0.717)	(0.916)
AR(p)	-1.405	0.271	0.267	0.554	0.016	-1.229	1.260	1.869	0.771	-0.751	0.420	2.862
	(0.086)	(0.606)	(0.604)	(0.708)	(0.506)	(0.115)	(0.891)	(0.964)	(0.776)	(0.230)	(0.661)	(0.996)
GETS	-1.435	0.428	0.427	0.707	0.286	-1.103	1.280	1.068	2.992	-0.740	0.548	1.692
	(0.081)	(0.664)	(0.664)	(0.757)	(0.611)	(0.140)	(0.895)	(0.853)	(0.997)	(0.233)	(0.706)	(0.949)
GETS-IIS	-1.164	0.453	0.448	0.765	0.301	-1.122	1.396	1.123	0.760	-0.626	0.577	2.010
	(0.127)	(0.673)	(0.671)	(0.775)	(0.617)	(0.136)	(0.913)	(0.864)	(0.773)	(0.268)	(0.716)	(0.973)
GETS-SIS	0.785	2.009	2.113	2.008	2.127	-0.511	1.761	1.779	1.532	1.016	2.246	1.899
	(0.781)	(0.973)	(0.978)	(0.973)	(0.979)	(0.307)	(0.955)	(0.957)	(0.932)	(0.841)	(0.984)	(0.966)
GETS-DDD	1.048	1.168	1.170	1.250	1.212	-0.387	1.582	2.280	1.683	1.151	1.280	1.980
	(0.848)	(0.874)	(0.874)	(0.889)	(0.882)	(0.351)	(0.938)	(0.985)	(0.948)	(0.870)	(0.895)	(0.971)
GETS-IIS-DDD	1.100	1.216	1.219	1.297	1.269	-0.391	1.633	2.499	1.767	1.199	1.336	2.113
	(0.860)	(0.883)	(0.883)	(0.897)	(0.893)	(0.349)	(0.943)	(0.991)	(0.956)	(0.880)	(0.904)	(0.978)
GETS-SIS-DDD	0.732	1.125	1.129	1.209	1.159	-0.540	1.609	2.296	1.558	0.916	1.260	1.955
	(0.765)	(0.865)	(0.866)	(0.882)	(0.872)	(0.297)	(0.941)	(0.985)	(0.935)	(0.816)	(0.891)	(0.970)
Ridge, CV	**-2.468**	0.314	0.308	0.560	0.144	-1.091	1.198	0.988	1.357	-1.016	0.419	1.397
	(0.010)	(0.622)	(0.620)	(0.710)	(0.557)	(0.142)	(0.880)	(0.834)	(0.907)	(0.159)	(0.661)	(0.913)
Lasso, CV	**-2.669**	0.364	0.357	0.601	0.218	-1.052	1.211	1.063	1.419	-0.775	0.464	1.413
	(0.006)	(0.641)	(0.638)	(0.724)	(0.585)	(0.151)	(0.882)	(0.851)	(0.916)	(0.222)	(0.677)	(0.916)
ELNET, CV	**-2.751**	0.361	0.354	0.597	0.215	-1.052	1.205	1.058	1.417	-0.785	0.461	1.403
	(0.005)	(0.640)	(0.637)	(0.722)	(0.584)	(0.151)	(0.881)	(0.850)	(0.916)	(0.219)	(0.676)	(0.914)
Ridge, AIC	-1.662	0.406	0.404	0.685	0.252	-1.119	1.236	1.243	1.340	-0.704	0.527	1.849
	(0.054)	(0.656)	(0.655)	(0.751)	(0.599)	(0.136)	(0.887)	(0.888)	(0.904)	(0.243)	(0.699)	(0.963)
Lasso, AIC	-1.492	0.399	0.396	0.708	0.225	-1.133	1.328	1.010	1.046	-0.831	0.518	1.582
	(0.073)	(0.654)	(0.652)	(0.758)	(0.588)	(0.133)	(0.902)	(0.840)	(0.848)	(0.206)	(0.696)	(0.938)
ELNET, AIC	-1.452	0.491	0.488	0.762	0.382	-1.062	1.276	1.319	1.558	-0.396	0.604	1.819
	(0.079)	(0.686)	(0.685)	(0.774)	(0.647)	(0.149)	(0.894)	(0.901)	(0.935)	(0.348)	(0.725)	(0.960)
k-NN	-1.174	0.384	0.376	0.569	0.271	-0.983	0.981	1.000	1.580	-0.194	0.474	1.115
	(0.125)	(0.648)	(0.645)	(0.713)	(0.606)	(0.167)	(0.833)	(0.837)	(0.937)	(0.424)	(0.680)	(0.863)
wk-NN	**-5.800**	-0.109	-0.111	0.088	-0.444	-1.324	0.696	0.055	-0.184	**-3.117**	0.027	0.354
	(0.000)	(0.457)	(0.456)	(0.535)	(0.330)	(0.098)	(0.754)	(0.522)	(0.428)	**(0.002)**	(0.511)	(0.637)
RF	**-3.051**	0.036	0.035	0.260	-0.227	-1.194	0.802	0.379	0.438	**-2.086**	0.155	0.722
	(0.002)	(0.514)	(0.514)	(0.601)	(0.411)	(0.121)	(0.785)	(0.646)	(0.668)	**(0.023)**	(0.561)	(0.762)
FFNN	-0.286	0.924	0.861	1.458	0.798	-0.984	2.512	1.130	1.176	0.183	0.956	1.578
	(0.388)	(0.818)	(0.802)	(0.922)	(0.784)	(0.167)	(0.991)	(0.866)	(0.875)	(0.572)	(0.826)	(0.937)
RNN	1.823	1.120	1.095	1.299	1.162	-0.310	1.338	1.639	2.083	1.550	1.137	1.726
	(0.960)	(0.864)	(0.859)	(0.898)	(0.872)	(0.380)	(0.904)	(0.944)	(0.977)	(0.934)	(0.867)	(0.952)
SVR-LIN	-1.033	0.479	0.465	0.779	0.321	-1.045	1.347	0.875	0.964	-0.413	0.564	1.230
	(0.155)	(0.682)	(0.677)	(0.779)	(0.625)	(0.152)	(0.906)	(0.806)	(0.828)	(0.341)	(0.711)	(0.886)
SVR-POLY	0.871	1.819	1.642	1.794	1.534	0.015	1.510	1.269	1.274	1.007	1.657	1.372
	(0.804)	(0.960)	(0.944)	(0.958)	(0.932)	(0.506)	(0.929)	(0.893)	(0.893)	(0.839)	(0.946)	(0.910)
SVR-RBF	0.156	0.655	0.656	0.857	0.620	-0.745	1.227	1.246	2.727	1.056	0.729	1.470
	(0.561)	(0.741)	(0.742)	(0.801)	(0.730)	(0.231)	(0.885)	(0.888)	(0.995)	(0.850)	(0.764)	(0.924)
SVR-ANOVA	-	0.690	0.682	0.902	0.662	-0.806	1.351	1.350	8.386	1.520	0.771	1.647
	-	(0.752)	(0.750)	(0.813)	(0.743)	(0.213)	(0.906)	(0.906)	(1.000)	(0.930)	(0.777)	(0.945)
AR+SVR-POLY	-0.690	-	-0.009	0.854	-0.672	-1.603	1.021	0.162	0.076	-0.492	0.598	0.291
	(0.248)	-	(0.497)	(0.800)	(0.254)	(0.060)	(0.842)	(0.564)	(0.530)	(0.313)	(0.723)	(0.614)
AR+SVR-RBF	-0.682	0.009	-	0.684	-0.648	-1.701	1.023	0.170	0.079	-0.489	1.023	0.301
	(0.250)	(0.503)	-	(0.750)	(0.261)	(0.050)	(0.842)	(0.567)	(0.531)	(0.314)	(0.843)	(0.617)
AR+SVR-ANOVA	-0.902	-0.854	-0.684	-	-1.158	-1.666	0.893	-0.063	-0.103	-0.721	-0.125	0.060
	(0.187)	(0.200)	(0.250)	-	(0.128)	(0.053)	(0.810)	(0.475)	(0.460)	(0.238)	(0.451)	(0.524)
AR+FFNN	-0.662	0.672	0.648	1.158	-	-1.429	1.173	0.704	0.363	-0.392	1.039	0.935
	(0.257)	(0.746)	(0.739)	(0.872)	-	(0.082)	(0.875)	(0.756)	(0.641)	(0.349)	(0.846)	(0.821)
AR+RNN	0.806	1.603	1.701	1.666	1.429	-	2.077	1.501	1.278	0.940	1.873	1.534
	(0.787)	(0.940)	(0.950)	(0.947)	(0.918)	-	(0.976)	(0.928)	(0.894)	(0.822)	(0.964)	(0.932)
Ave. BM	-1.351	-1.021	-1.023	-0.893	-1.173	**-2.077**	-	-0.900	-0.654	-1.213	-0.802	-0.806
	(0.094)	(0.158)	(0.158)	(0.190)	(0.125)	**(0.024)**	-	(0.188)	(0.259)	(0.118)	(0.215)	(0.213)
Ave. Linear	-1.350	-0.162	-0.170	0.063	-0.704	-1.501	0.900	-	-0.111	-0.984	0.007	0.535
	(0.094)	(0.436)	(0.433)	(0.525)	(0.244)	(0.072)	(0.812)	-	(0.456)	(0.167)	(0.503)	(0.701)
Ave. Local	**-8.386**	-0.076	-0.079	0.103	-0.363	-1.278	0.654	0.111	-	**-2.333**	0.046	0.363
	(0.000)	(0.470)	(0.469)	(0.540)	(0.359)	(0.106)	(0.741)	(0.544)	-	**(0.014)**	(0.518)	(0.640)
Ave. Non-linear	-1.520	0.492	0.489	0.721	0.392	-0.940	1.213	0.984	2.333	-	0.577	1.298
	(0.070)	(0.687)	(0.686)	(0.762)	(0.651)	(0.178)	(0.882)	(0.833)	(0.986)	-	(0.716)	(0.897)
Ave. AR+	-0.771	-0.598	-1.023	0.125	-1.039	**-1.873**	0.802	-0.007	-0.046	-0.577	-	0.112
	(0.223)	(0.277)	(0.157)	(0.549)	(0.154)	**(0.036)**	(0.785)	(0.497)	(0.482)	(0.284)	-	(0.544)
Tot. Ave.	-1.647	-0.291	-0.301	-0.060	-0.935	-1.534	0.806	-0.535	-0.363	-1.298	-0.112	-
	(0.055)	(0.386)	(0.383)	(0.476)	(0.179)	(0.068)	(0.787)	(0.299)	(0.360)	(0.103)	(0.456)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.10: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 4$. $N = 28$.

	AR(1)	RW	DDD	AR(p)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.774	-0.419	-1.027	-1.079	-1.065	-1.309	**-2.154**	**-2.153**	**-1.871**	-0.824	-0.881
	-	(0.223)	(0.339)	(0.157)	(0.145)	(0.148)	(0.101)	**(0.020)**	**(0.020)**	**(0.036)**	(0.209)	(0.193)
RW	0.774	-	1.022	0.131	0.209	0.181	**-1.889**	0.141	0.110	0.068	0.315	0.258
	(0.777)	-	(0.842)	(0.552)	(0.582)	(0.571)	**(0.035)**	(0.556)	(0.543)	(0.527)	(0.622)	(0.601)
DDD	0.419	-1.022	-	**-2.731**	-0.321	-0.363	-1.418	-0.800	-0.792	-0.843	-0.193	-0.257
	(0.661)	(0.158)	-	**(0.005)**	(0.375)	(0.360)	(0.084)	(0.215)	(0.218)	(0.203)	(0.424)	(0.399)
AR(p)	1.027	-0.131	2.731	-	0.883	0.878	-1.019	-0.187	-0.194	-0.150	1.296	1.246
	(0.843)	(0.448)	(0.995)	-	(0.807)	(0.806)	(0.159)	(0.426)	(0.424)	(0.441)	(0.897)	(0.888)
GETS	1.079	-0.209	0.321	-0.883	-	-0.931	-1.098	-0.371	-0.374	-0.352	0.857	0.457
	(0.855)	(0.418)	(0.625)	(0.193)	-	(0.180)	(0.141)	(0.357)	(0.356)	(0.364)	(0.801)	(0.674)
GETS-IIS	1.065	-0.181	0.363	-0.878	0.931	-	-1.066	-0.308	-0.313	-0.284	1.081	0.797
	(0.852)	(0.429)	(0.640)	(0.194)	(0.820)	-	(0.148)	(0.380)	(0.378)	(0.389)	(0.855)	(0.784)
GETS-SIS	1.309	1.889	1.418	1.019	1.098	1.066	-	0.811	0.796	0.962	1.230	1.160
	(0.899)	(0.965)	(0.916)	(0.841)	(0.859)	(0.852)	-	(0.788)	(0.784)	(0.828)	(0.885)	(0.872)
GETS-DDD	2.154	-0.141	0.800	0.187	0.371	0.308	-0.811	-	-0.505	0.360	0.525	0.425
	(0.980)	(0.444)	(0.785)	(0.574)	(0.643)	(0.620)	(0.212)	-	(0.309)	(0.639)	(0.698)	(0.663)
GETS-IIS-DDD	2.153	-0.110	0.792	0.194	0.374	0.313	-0.796	0.505	-	0.384	0.526	0.428
	(0.980)	(0.457)	(0.782)	(0.576)	(0.644)	(0.622)	(0.216)	(0.691)	-	(0.648)	(0.699)	(0.664)
GETS-SIS-DDD	1.871	-0.068	0.843	0.150	0.352	0.284	-0.962	-0.360	-0.384	-	0.521	0.414
	(0.964)	(0.473)	(0.797)	(0.559)	(0.636)	(0.611)	(0.172)	(0.361)	(0.352)	-	(0.697)	(0.659)
Ridge, CV	0.824	-0.315	0.193	-1.296	-0.857	-1.081	-1.230	-0.525	-0.526	-0.521	-	-1.212
	(0.791)	(0.378)	(0.576)	(0.103)	(0.199)	(0.145)	(0.115)	(0.302)	(0.301)	(0.303)	-	(0.118)
Lasso, CV	0.881	-0.258	0.257	-1.246	-0.457	-0.797	-1.160	-0.425	-0.428	-0.414	1.212	-
	(0.807)	(0.399)	(0.601)	(0.112)	(0.326)	(0.216)	(0.128)	(0.337)	(0.336)	(0.341)	(0.882)	-
ELNET, CV	0.878	-0.274	0.236	-1.342	-0.678	-1.023	-1.175	-0.458	-0.460	-0.450	1.070	-0.989
	(0.806)	(0.393)	(0.592)	(0.095)	(0.252)	(0.158)	(0.125)	(0.325)	(0.325)	(0.328)	(0.853)	(0.166)
Ridge, AIC	0.812	-0.310	0.193	-1.503	-0.943	-1.217	-1.268	-0.523	-0.524	-0.522	0.056	-1.075
	(0.788)	(0.379)	(0.576)	(0.072)	(0.177)	(0.117)	(0.108)	(0.303)	(0.302)	(0.303)	(0.522)	(0.146)
Lasso, AIC	0.798	-0.292	0.209	-1.585	-0.788	-1.122	-1.228	-0.497	-0.499	-0.495	0.501	-0.688
	(0.784)	(0.386)	(0.582)	(0.062)	(0.219)	(0.136)	(0.115)	(0.311)	(0.311)	(0.312)	(0.690)	(0.249)
ELNET, AIC	0.810	-0.316	0.182	-1.431	-0.996	-1.221	-1.276	-0.526	-0.527	-0.523	-0.192	-1.275
	(0.788)	(0.377)	(0.571)	(0.082)	(0.164)	(0.116)	(0.106)	(0.302)	(0.301)	(0.303)	(0.425)	(0.107)
k-NN	0.798	-0.414	0.202	-0.680	-0.472	-0.555	-1.231	-0.752	-0.747	-0.761	-0.234	-0.439
	(0.784)	(0.341)	(0.579)	(0.251)	(0.320)	(0.292)	(0.115)	(0.229)	(0.231)	(0.227)	(0.408)	(0.332)
wk-NN	0.200	-0.664	-0.267	-1.249	-1.212	-1.236	-1.497	-1.517	-1.494	-1.564	-1.383	-1.303
	(0.578)	(0.256)	(0.396)	(0.111)	(0.118)	(0.114)	(0.073)	(0.070)	(0.073)	(0.065)	(0.089)	(0.102)
RF	0.446	-0.543	-0.026	-0.938	-0.754	-0.826	-1.321	-1.120	-1.105	-1.193	-0.621	-0.738
	(0.670)	(0.296)	(0.490)	(0.178)	(0.229)	(0.208)	(0.099)	(0.136)	(0.140)	(0.122)	(0.270)	(0.233)
FFNN	0.445	-0.503	-0.112	-0.952	-0.954	-0.956	-1.257	-0.887	-0.884	-0.898	-0.653	-0.735
	(0.670)	(0.309)	(0.456)	(0.175)	(0.174)	(0.174)	(0.110)	(0.192)	(0.192)	(0.189)	(0.260)	(0.234)
RNN	1.635	-0.284	0.212	-0.353	-0.201	-0.261	-1.187	-1.437	-1.436	-1.110	0.054	-0.078
	(0.943)	(0.389)	(0.583)	(0.364)	(0.421)	(0.398)	(0.123)	(0.081)	(0.081)	(0.138)	(0.521)	(0.469)
SVR-LIN	1.062	-0.129	1.706	0.038	0.633	0.461	-0.840	-0.176	-0.183	-0.494	0.864	0.725
	(0.851)	(0.449)	(0.950)	(0.515)	(0.734)	(0.676)	(0.204)	(0.431)	(0.428)	(0.313)	(0.803)	(0.763)
SVR-POLY	0.944	-0.187	0.368	-0.369	0.170	-0.018	-0.935	-0.262	-0.267	-0.994	0.619	0.411
	(0.823)	(0.426)	(0.642)	(0.357)	(0.567)	(0.493)	(0.179)	(0.398)	(0.396)	(0.165)	(0.729)	(0.658)
SVR-RBF	0.743	-0.057	0.813	0.277	0.423	0.377	-0.804	-0.028	-0.037	0.027	0.684	0.608
	(0.768)	(0.477)	(0.788)	(0.608)	(0.662)	(0.646)	(0.214)	(0.489)	(0.485)	(0.511)	(0.750)	(0.726)
SVR-ANOVA	1.017	1.135	1.021	0.996	0.986	0.987	0.198	0.714	0.709	0.757	1.067	1.056
	(0.841)	(0.867)	(0.842)	(0.836)	(0.834)	(0.834)	(0.578)	(0.759)	(0.758)	(0.772)	(0.852)	(0.850)
AR+SVR-POLY	1.124	-0.246	0.248	-0.229	-0.091	-0.144	-1.240	-1.495	-1.512	-1.196	0.102	0.004
	(0.864)	(0.404)	(0.597)	(0.410)	(0.464)	(0.443)	(0.113)	(0.073)	(0.071)	(0.121)	(0.540)	(0.502)
AR+SVR-RBF	1.029	-0.223	0.273	-0.199	-0.048	-0.106	-1.336	-0.837	-0.838	-0.805	0.150	0.046
	(0.844)	(0.412)	(0.607)	(0.422)	(0.481)	(0.458)	(0.096)	(0.205)	(0.205)	(0.214)	(0.559)	(0.518)
AR+SVR-ANOVA	1.475	-0.044	0.560	0.187	0.411	0.326	-1.088	-0.051	-0.083	0.147	0.585	0.455
	(0.924)	(0.483)	(0.710)	(0.574)	(0.658)	(0.626)	(0.143)	(0.480)	(0.467)	(0.558)	(0.718)	(0.673)
AR+FFNN	1.165	-0.141	1.716	-0.024	0.122	0.067	-1.017	-0.307	-0.319	-0.246	0.285	0.190
	(0.873)	(0.444)	(0.951)	(0.491)	(0.548)	(0.526)	(0.159)	(0.380)	(0.376)	(0.404)	(0.611)	(0.575)
AR+RNN	1.226	0.861	1.284	0.677	0.764	0.732	0.224	0.668	0.662	0.692	0.872	0.812
	(0.885)	(0.802)	(0.895)	(0.748)	(0.774)	(0.765)	(0.588)	(0.745)	(0.743)	(0.753)	(0.804)	(0.788)
Ave. BM	-0.474	-1.615	-1.636	-1.148	-1.121	-1.134	-1.633	-1.152	-1.140	-1.211	-1.122	-1.130
	(0.320)	(0.059)	(0.057)	(0.131)	(0.136)	(0.133)	(0.057)	(0.130)	(0.132)	(0.118)	(0.136)	(0.134)
Ave. Linear	0.177	-0.543	-0.176	-1.247	-1.058	-1.120	**-1.714**	**-2.058**	**-1.984**	**-2.638**	-1.069	-1.128
	(0.570)	(0.296)	(0.431)	(0.112)	(0.150)	(0.136)	**(0.049)**	**(0.025)**	**(0.029)**	**(0.007)**	(0.147)	(0.135)
Ave. Local	0.348	-0.599	-0.135	-1.074	-0.942	-0.997	-1.416	-1.198	-1.183	-1.252	-0.966	-1.006
	(0.635)	(0.277)	(0.447)	(0.146)	(0.177)	(0.164)	(0.084)	(0.121)	(0.124)	(0.111)	(0.171)	(0.162)
Ave. Non-linear	0.806	-0.219	0.322	-0.871	-0.030	-0.247	-1.032	-1.173	-1.212	-1.024	0.555	0.310
	(0.786)	(0.414)	(0.625)	(0.196)	(0.488)	(0.403)	(0.156)	(0.126)	(0.118)	(0.157)	(0.708)	(0.620)
Ave. AR+	0.584	-0.334	0.851	-0.367	-0.253	-0.295	-1.536	-0.850	-0.854	-0.832	-0.079	-0.158
	(0.718)	(0.371)	(0.799)	(0.358)	(0.401)	(0.385)	(0.068)	(0.201)	(0.200)	(0.206)	(0.469)	(0.438)
Tot. Ave.	0.277	-0.526	-0.140	-1.364	-1.206	-1.262	-1.679	**-3.579**	**-3.253**	-1.077	-1.199	-1.227
	(0.608)	(0.302)	(0.445)	(0.092)	(0.119)	(0.109)	(0.052)	**(0.001)**	**(0.002)**	(0.146)	(0.120)	(0.115)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.11: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 4$. $N = 28$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	-0.878	-0.812	-0.798	-0.810	-0.798	-0.200	-0.446	-0.445	-1.635	-1.062	-0.944	-0.743
	(0.194)	(0.212)	(0.216)	(0.212)	(0.216)	(0.422)	(0.330)	(0.330)	(0.057)	(0.149)	(0.177)	(0.232)
RW	0.274	0.310	0.292	0.316	0.414	0.664	0.543	0.503	0.284	0.129	0.187	0.057
	(0.607)	(0.621)	(0.614)	(0.623)	(0.659)	(0.744)	(0.704)	(0.691)	(0.611)	(0.551)	(0.574)	(0.523)
DDD	-0.236	-0.193	-0.209	-0.182	-0.202	0.267	0.026	0.112	-0.212	**-1.706**	-0.368	-0.813
	(0.408)	(0.424)	(0.418)	(0.429)	(0.421)	(0.604)	(0.510)	(0.544)	(0.417)	**(0.050)**	(0.358)	(0.212)
AR(p)	1.342	1.503	1.585	1.431	0.680	1.249	0.938	0.952	0.353	-0.038	0.369	-0.277
	(0.905)	(0.928)	(0.938)	(0.918)	(0.749)	(0.889)	(0.822)	(0.825)	(0.636)	(0.485)	(0.643)	(0.392)
GETS	0.678	0.943	0.788	0.996	0.472	1.212	0.754	0.954	0.201	-0.633	-0.170	-0.423
	(0.748)	(0.823)	(0.781)	(0.836)	(0.680)	(0.882)	(0.771)	(0.826)	(0.579)	(0.266)	(0.433)	(0.338)
GETS-IIS	1.023	1.217	1.122	1.221	0.555	1.236	0.826	0.956	0.261	-0.461	0.018	-0.377
	(0.842)	(0.883)	(0.864)	(0.884)	(0.708)	(0.886)	(0.792)	(0.826)	(0.602)	(0.324)	(0.507)	(0.354)
GETS-SIS	1.175	1.268	1.228	1.276	1.231	1.497	1.321	1.257	1.187	0.840	0.935	0.804
	(0.875)	(0.892)	(0.885)	(0.894)	(0.885)	(0.927)	(0.901)	(0.890)	(0.877)	(0.796)	(0.821)	(0.786)
GETS-DDD	0.458	0.523	0.497	0.526	0.752	1.517	1.120	0.887	1.437	0.176	0.262	0.028
	(0.675)	(0.697)	(0.689)	(0.698)	(0.771)	(0.930)	(0.864)	(0.808)	(0.919)	(0.569)	(0.602)	(0.511)
GETS-IIS-DDD	0.460	0.524	0.499	0.527	0.747	1.494	1.105	0.884	1.436	0.183	0.267	0.037
	(0.675)	(0.698)	(0.689)	(0.699)	(0.769)	(0.927)	(0.860)	(0.808)	(0.919)	(0.572)	(0.604)	(0.515)
GETS-SIS-DDD	0.450	0.522	0.495	0.523	0.761	1.564	1.193	0.898	1.110	0.494	0.994	-0.027
	(0.672)	(0.697)	(0.688)	(0.697)	(0.773)	(0.935)	(0.878)	(0.811)	(0.862)	(0.687)	(0.835)	(0.489)
Ridge, CV	-1.070	-0.056	-0.501	0.192	0.234	1.383	0.621	0.653	-0.054	-0.864	-0.619	-0.684
	(0.147)	(0.478)	(0.310)	(0.575)	(0.592)	(0.911)	(0.730)	(0.740)	(0.479)	(0.197)	(0.271)	(0.250)
Lasso, CV	0.989	1.075	0.688	1.275	0.439	1.303	0.738	0.735	0.078	-0.725	-0.411	-0.608
	(0.834)	(0.854)	(0.751)	(0.893)	(0.668)	(0.898)	(0.767)	(0.766)	(0.531)	(0.237)	(0.342)	(0.274)
ELNET, CV	-	0.808	0.353	1.240	0.383	1.338	0.692	0.720	0.039	-0.815	-0.504	-0.626
	-	(0.787)	(0.637)	(0.887)	(0.648)	(0.904)	(0.753)	(0.761)	(0.516)	(0.211)	(0.309)	(0.268)
Ridge, AIC	-0.808	-	-0.399	0.465	0.199	1.197	0.595	0.646	-0.046	-0.875	-0.599	-0.684
	(0.213)	-	(0.346)	(0.677)	(0.578)	(0.879)	(0.722)	(0.738)	(0.482)	(0.195)	(0.277)	(0.250)
Lasso, AIC	-0.353	0.399	-	0.532	0.214	1.046	0.589	0.649	-0.009	-0.899	-0.600	-0.695
	(0.363)	(0.654)	-	(0.700)	(0.584)	(0.848)	(0.720)	(0.739)	(0.497)	(0.188)	(0.277)	(0.246)
ELNET, AIC	-1.240	-0.465	-0.532	-	0.134	1.055	0.546	0.649	-0.066	-0.926	-0.654	-0.693
	(0.113)	(0.323)	(0.300)	-	(0.553)	(0.850)	(0.705)	(0.739)	(0.474)	(0.181)	(0.259)	(0.247)
k-NN	-0.383	-0.199	-0.214	-0.134	-	2.362	0.568	0.711	-0.185	-0.566	-0.470	-0.689
	(0.352)	(0.422)	(0.416)	(0.447)	-	(0.987)	(0.713)	(0.759)	(0.427)	(0.288)	(0.321)	(0.248)
wk-NN	-1.338	-1.197	-1.046	-1.055	**-2.362**	-	-0.677	-0.279	-1.237	-1.115	-1.055	-1.038
	(0.096)	(0.121)	(0.152)	(0.150)	**(0.013)**	-	(0.252)	(0.391)	(0.113)	(0.137)	(0.150)	(0.154)
RF	-0.692	-0.595	-0.589	-0.546	-0.568	0.677	-	0.198	-0.457	-0.795	-0.715	-0.833
	(0.247)	(0.278)	(0.280)	(0.295)	(0.287)	(0.748)	-	(0.578)	(0.326)	(0.217)	(0.240)	(0.206)
FFNN	-0.720	-0.646	-0.649	-0.649	-0.711	0.279	-0.198	-	-0.898	-0.959	-0.815	-0.682
	(0.239)	(0.262)	(0.261)	(0.261)	(0.241)	(0.609)	(0.422)	-	(0.189)	(0.173)	(0.211)	(0.250)
RNN	-0.039	0.046	0.009	0.066	0.185	1.237	0.457	0.898	-	-0.333	-0.218	-0.348
	(0.484)	(0.518)	(0.503)	(0.526)	(0.573)	(0.887)	(0.674)	(0.811)	-	(0.371)	(0.415)	(0.365)
SVR-LIN	0.815	0.875	0.899	0.926	0.566	1.115	0.795	0.959	0.333	-	0.883	-0.207
	(0.789)	(0.805)	(0.812)	(0.819)	(0.712)	(0.863)	(0.783)	(0.827)	(0.629)	-	(0.807)	(0.419)
SVR-POLY	0.504	0.599	0.600	0.654	0.470	1.055	0.715	0.815	0.218	-0.883	-	-0.425
	(0.691)	(0.723)	(0.723)	(0.741)	(0.679)	(0.850)	(0.760)	(0.789)	(0.585)	(0.193)	-	(0.337)
SVR-RBF	0.626	0.684	0.695	0.693	0.689	1.038	0.833	0.682	0.348	0.207	0.425	-
	(0.732)	(0.750)	(0.754)	(0.753)	(0.752)	(0.846)	(0.794)	(0.750)	(0.635)	(0.581)	(0.663)	-
SVR-ANOVA	1.059	1.076	1.090	1.076	0.960	1.111	1.066	0.992	0.788	0.988	1.053	1.291
	(0.850)	(0.854)	(0.857)	(0.854)	(0.827)	(0.862)	(0.852)	(0.835)	(0.781)	(0.834)	(0.849)	(0.896)
AR+SVR-POLY	0.034	0.102	0.069	0.116	0.202	0.811	0.398	0.669	0.147	-0.214	-0.113	-0.259
	(0.513)	(0.540)	(0.527)	(0.546)	(0.579)	(0.788)	(0.653)	(0.745)	(0.558)	(0.416)	(0.455)	(0.399)
AR+SVR-RBF	0.077	0.151	0.116	0.168	0.297	0.968	0.467	0.690	0.325	-0.180	-0.082	-0.242
	(0.530)	(0.559)	(0.546)	(0.566)	(0.616)	(0.829)	(0.678)	(0.752)	(0.626)	(0.429)	(0.468)	(0.405)
AR+SVR-ANOVA	0.495	0.609	0.551	0.637	0.732	1.356	0.842	1.169	1.004	0.152	0.264	0.009
	(0.688)	(0.726)	(0.707)	(0.735)	(0.765)	(0.907)	(0.796)	(0.874)	(0.838)	(0.560)	(0.603)	(0.504)
AR+FFNN	0.219	0.290	0.254	0.307	0.390	0.873	0.531	0.818	0.475	-0.029	0.060	-0.108
	(0.586)	(0.613)	(0.599)	(0.619)	(0.650)	(0.805)	(0.700)	(0.790)	(0.681)	(0.489)	(0.524)	(0.457)
AR+RNN	0.829	0.853	0.831	0.862	0.996	1.218	1.043	1.087	1.117	0.643	0.709	0.562
	(0.793)	(0.799)	(0.793)	(0.802)	(0.836)	(0.883)	(0.847)	(0.857)	(0.863)	(0.737)	(0.758)	(0.711)
Ave. BM	-1.122	-1.077	-1.030	-1.045	**-2.006**	-1.312	-1.436	-0.950	**-2.350**	-1.050	-1.042	-1.014
	(0.136)	(0.146)	(0.156)	(0.153)	**(0.027)**	(0.100)	(0.081)	(0.175)	**(0.013)**	(0.151)	(0.153)	(0.160)
Ave. Linear	-1.078	-1.034	-0.973	-0.977	-0.815	0.127	-0.722	-0.125	-0.842	-0.952	-0.870	-1.016
	(0.145)	(0.155)	(0.170)	(0.169)	(0.211)	(0.550)	(0.238)	(0.451)	(0.204)	(0.175)	(0.196)	(0.159)
Ave. Local	-0.988	-0.872	-0.794	-0.774	**-2.068**	1.169	-0.413	0.039	-0.725	-0.922	-0.861	-0.952
	(0.166)	(0.196)	(0.217)	(0.223)	**(0.024)**	(0.874)	(0.341)	(0.515)	(0.237)	(0.182)	(0.198)	(0.175)
Ave. Non-linear	0.405	0.537	0.548	0.582	0.430	1.051	0.704	0.678	0.145	-0.700	-0.346	-0.676
	(0.656)	(0.702)	(0.706)	(0.717)	(0.665)	(0.849)	(0.756)	(0.748)	(0.557)	(0.245)	(0.366)	(0.253)
Ave. AR+	-0.134	-0.085	-0.105	-0.073	-0.031	0.462	0.169	0.320	-0.235	-0.327	-0.243	-0.358
	(0.447)	(0.467)	(0.459)	(0.471)	(0.488)	(0.676)	(0.566)	(0.624)	(0.408)	(0.373)	(0.405)	(0.361)
Tot. Ave.	-1.188	-1.165	-1.067	-1.109	-0.731	0.162	-0.573	-0.059	-0.882	-1.026	-0.934	-0.990
	(0.123)	(0.127)	(0.148)	(0.139)	(0.236)	(0.564)	(0.286)	(0.477)	(0.193)	(0.157)	(0.179)	(0.165)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.12: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Univariate. $h = 4$. $N = 28$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.017	-1.124	-1.029	-1.475	-1.165	-1.226	0.474	-0.177	-0.348	-0.806	-0.584	-0.277
	(0.159)	(0.136)	(0.156)	(0.076)	(0.127)	(0.115)	(0.680)	(0.430)	(0.365)	(0.214)	(0.282)	(0.392)
RW	-1.135	0.246	0.223	0.044	0.141	-0.861	1.615	0.543	0.599	0.219	0.334	0.526
	(0.133)	(0.596)	(0.588)	(0.517)	(0.556)	(0.198)	(0.941)	(0.704)	(0.723)	(0.586)	(0.629)	(0.698)
DDD	-1.021	-0.248	-0.273	-0.560	**-1.716**	-1.284	1.636	0.176	0.135	-0.322	-0.851	0.140
	(0.158)	(0.403)	(0.393)	(0.290)	**(0.049)**	(0.105)	(0.943)	(0.569)	(0.553)	(0.375)	(0.201)	(0.555)
AR(p)	-0.996	0.229	0.199	-0.187	0.024	-0.677	1.148	1.247	1.074	0.871	0.367	1.364
	(0.164)	(0.590)	(0.578)	(0.426)	(0.509)	(0.252)	(0.869)	(0.888)	(0.854)	(0.804)	(0.642)	(0.908)
GETS	-0.986	0.091	0.048	-0.411	-0.122	-0.764	1.121	1.058	0.942	0.030	0.253	1.206
	(0.166)	(0.536)	(0.519)	(0.342)	(0.452)	(0.226)	(0.864)	(0.850)	(0.823)	(0.512)	(0.599)	(0.881)
GETS-IIS	-0.987	0.144	0.106	-0.326	-0.067	-0.732	1.134	1.120	0.997	0.247	0.295	1.262
	(0.166)	(0.557)	(0.542)	(0.374)	(0.474)	(0.235)	(0.867)	(0.864)	(0.836)	(0.597)	(0.615)	(0.891)
GETS-SIS	-0.198	1.240	1.336	1.088	1.017	-0.224	1.633	1.714	1.416	1.032	1.536	1.679
	(0.422)	(0.887)	(0.904)	(0.857)	(0.841)	(0.412)	(0.943)	(0.951)	(0.916)	(0.844)	(0.932)	(0.948)
GETS-DDD	-0.714	1.495	0.837	0.051	0.307	-0.668	1.152	2.058	1.198	1.173	0.850	3.579
	(0.241)	(0.927)	(0.795)	(0.520)	(0.620)	(0.255)	(0.870)	(0.975)	(0.879)	(0.874)	(0.799)	(0.999)
GETS-IIS-DDD	-0.709	1.512	0.838	0.083	0.319	-0.662	1.140	1.984	1.183	1.212	0.854	3.253
	(0.242)	(0.929)	(0.795)	(0.533)	(0.624)	(0.257)	(0.868)	(0.971)	(0.876)	(0.882)	(0.800)	(0.998)
GETS-SIS-DDD	-0.757	1.196	0.805	-0.147	0.246	-0.692	1.211	2.638	1.252	1.024	0.832	1.077
	(0.228)	(0.879)	(0.786)	(0.442)	(0.596)	(0.247)	(0.882)	(0.993)	(0.889)	(0.843)	(0.794)	(0.854)
Ridge, CV	-1.067	-0.102	-0.150	-0.585	-0.285	-0.872	1.122	1.069	0.966	-0.555	0.079	1.199
	(0.148)	(0.460)	(0.441)	(0.282)	(0.389)	(0.196)	(0.864)	(0.853)	(0.829)	(0.292)	(0.531)	(0.880)
Lasso, CV	-1.056	-0.004	-0.046	-0.455	-0.190	-0.812	1.130	1.128	1.006	-0.310	0.158	1.227
	(0.150)	(0.498)	(0.482)	(0.327)	(0.425)	(0.212)	(0.866)	(0.865)	(0.838)	(0.380)	(0.562)	(0.885)
ELNET, CV	-1.059	-0.034	-0.077	-0.495	-0.219	-0.829	1.122	1.078	0.988	-0.405	0.134	1.188
	(0.150)	(0.487)	(0.470)	(0.312)	(0.414)	(0.207)	(0.864)	(0.855)	(0.834)	(0.344)	(0.553)	(0.877)
Ridge, AIC	-1.076	-0.102	-0.151	-0.609	-0.290	-0.853	1.077	1.034	0.872	-0.537	0.085	1.165
	(0.146)	(0.460)	(0.441)	(0.274)	(0.387)	(0.201)	(0.854)	(0.845)	(0.804)	(0.298)	(0.533)	(0.873)
Lasso, AIC	-1.090	-0.069	-0.116	-0.551	-0.254	-0.831	1.030	0.973	0.794	-0.548	0.105	1.067
	(0.143)	(0.473)	(0.454)	(0.293)	(0.401)	(0.207)	(0.844)	(0.830)	(0.783)	(0.294)	(0.541)	(0.852)
ELNET, AIC	-1.076	-0.116	-0.168	-0.637	-0.307	-0.862	1.045	0.977	0.774	-0.582	0.073	1.109
	(0.146)	(0.454)	(0.434)	(0.265)	(0.381)	(0.198)	(0.847)	(0.831)	(0.777)	(0.283)	(0.529)	(0.861)
k-NN	-0.960	-0.202	-0.297	-0.732	-0.390	-0.996	2.006	0.815	2.068	-0.430	0.031	0.731
	(0.173)	(0.421)	(0.384)	(0.235)	(0.350)	(0.164)	(0.973)	(0.789)	(0.976)	(0.335)	(0.512)	(0.764)
wk-NN	-1.111	-0.811	-0.968	-1.356	-0.873	-1.218	1.312	-0.127	-1.169	-1.051	-0.462	-0.162
	(0.138)	(0.212)	(0.171)	(0.093)	(0.195)	(0.117)	(0.900)	(0.450)	(0.126)	(0.151)	(0.324)	(0.436)
RF	-1.066	-0.398	-0.467	-0.842	-0.531	-1.043	1.436	0.722	0.413	-0.704	-0.169	0.573
	(0.148)	(0.347)	(0.322)	(0.204)	(0.300)	(0.153)	(0.919)	(0.762)	(0.659)	(0.244)	(0.434)	(0.714)
FFNN	-0.992	-0.669	-0.690	-1.169	-0.818	-1.087	0.950	0.125	-0.039	-0.678	-0.320	0.059
	(0.165)	(0.255)	(0.248)	(0.126)	(0.210)	(0.143)	(0.825)	(0.549)	(0.485)	(0.252)	(0.376)	(0.523)
RNN	-0.788	-0.147	-0.325	-1.004	-0.475	-1.117	2.350	0.842	0.725	-0.145	0.235	0.882
	(0.219)	(0.442)	(0.374)	(0.162)	(0.319)	(0.137)	(0.987)	(0.796)	(0.763)	(0.443)	(0.592)	(0.807)
SVR-LIN	-0.988	0.214	0.180	-0.152	0.029	-0.643	1.050	0.952	0.922	0.700	0.327	1.026
	(0.166)	(0.584)	(0.571)	(0.440)	(0.511)	(0.263)	(0.849)	(0.825)	(0.818)	(0.755)	(0.627)	(0.843)
SVR-POLY	-1.053	0.113	0.082	-0.264	-0.060	-0.709	1.042	0.870	0.861	0.346	0.243	0.934
	(0.151)	(0.545)	(0.532)	(0.397)	(0.476)	(0.242)	(0.847)	(0.804)	(0.802)	(0.634)	(0.595)	(0.821)
SVR-RBF	-1.291	0.259	0.242	-0.009	0.108	-0.562	1.014	1.016	0.952	0.676	0.358	0.990
	(0.104)	(0.601)	(0.595)	(0.496)	(0.543)	(0.289)	(0.840)	(0.841)	(0.825)	(0.747)	(0.639)	(0.835)
SVR-ANOVA	-	0.706	0.709	0.602	0.604	-0.026	1.118	1.132	1.083	1.144	0.763	1.130
	-	(0.757)	(0.758)	(0.724)	(0.725)	(0.490)	(0.863)	(0.866)	(0.856)	(0.869)	(0.774)	(0.866)
AR+SVR-POLY	-0.706	-	-0.210	-1.440	-1.059	-1.062	1.739	0.697	0.563	-0.063	0.859	0.681
	(0.243)	-	(0.418)	(0.081)	(0.150)	(0.149)	(0.953)	(0.754)	(0.711)	(0.475)	(0.801)	(0.749)
AR+SVR-RBF	-0.709	0.210	-	-1.231	-0.536	-1.105	1.840	0.845	0.679	-0.030	1.281	0.820
	(0.242)	(0.582)	-	(0.114)	(0.298)	(0.140)	(0.962)	(0.797)	(0.748)	(0.488)	(0.895)	(0.790)
AR+SVR-ANOVA	-0.602	1.440	1.231	-	0.532	-0.801	1.682	1.226	1.060	0.316	1.717	1.291
	(0.276)	(0.919)	(0.886)	-	(0.701)	(0.215)	(0.948)	(0.885)	(0.851)	(0.623)	(0.951)	(0.896)
AR+FFNN	-0.604	1.059	0.536	-0.532	-	-0.955	1.443	0.808	0.677	0.104	1.623	0.797
	(0.275)	(0.850)	(0.702)	(0.299)	-	(0.174)	(0.920)	(0.787)	(0.748)	(0.541)	(0.942)	(0.784)
AR+RNN	0.026	1.062	1.105	0.801	0.955	-	1.791	1.189	1.132	0.728	1.249	1.156
	(0.510)	(0.851)	(0.860)	(0.785)	(0.826)	-	(0.958)	(0.878)	(0.866)	(0.763)	(0.889)	(0.871)
Ave. BM	-1.118	**-1.739**	**-1.840**	-1.682	-1.443	**-1.791**	-	-1.193	-1.428	-1.024	-1.143	-1.162
	(0.137)	**(0.047)**	**(0.038)**	(0.052)	(0.080)	**(0.042)**	-	(0.122)	(0.082)	(0.158)	(0.132)	(0.128)
Ave. Linear	-1.132	-0.697	-0.845	-1.226	-0.808	-1.189	1.193	-	-0.688	-0.888	-0.421	-0.347
	(0.134)	(0.246)	(0.203)	(0.115)	(0.213)	(0.122)	(0.878)	-	(0.249)	(0.191)	(0.338)	(0.365)
Ave. Local	-1.083	-0.563	-0.679	-1.060	-0.677	-1.132	1.428	0.688	-	-0.865	-0.291	0.789
	(0.144)	(0.289)	(0.252)	(0.149)	(0.252)	(0.134)	(0.918)	(0.751)	-	(0.197)	(0.387)	(0.782)
Ave. Non-linear	-1.144	0.063	0.030	-0.316	-0.104	-0.728	1.024	0.888	0.865	-	0.196	0.931
	(0.131)	(0.525)	(0.512)	(0.377)	(0.459)	(0.237)	(0.842)	(0.809)	(0.803)	-	(0.577)	(0.820)
Ave. AR+	-0.763	-0.859	-1.281	**-1.717**	-1.623	-1.249	1.143	0.421	0.291	-0.196	-	0.380
	(0.226)	(0.199)	(0.105)	**(0.049)**	(0.058)	(0.111)	(0.868)	(0.662)	(0.613)	(0.423)	-	(0.647)
Tot. Ave.	-1.130	-0.681	-0.820	-1.291	-0.797	-1.156	1.162	0.347	-0.789	-0.931	-0.380	-
	(0.134)	(0.251)	(0.210)	(0.104)	(0.216)	(0.129)	(0.872)	(0.635)	(0.218)	(0.180)	(0.353)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.13: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 0$. $N = 31$. Computed at origin T.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.520	-0.530	0.591	-1.465	-1.658	-1.674	-1.399	-1.416	-1.487	1.340	1.466
	-	(0.304)	(0.300)	(0.721)	(0.076)	(0.054)	(0.052)	(0.086)	(0.083)	(0.074)	(0.905)	(0.924)
RW	0.520	-	-0.039	1.073	-1.331	-1.563	-1.618	-1.281	-1.296	-1.399	1.960	1.877
	(0.696)	-	(0.485)	(0.854)	(0.096)	(0.064)	(0.058)	(0.105)	(0.102)	(0.086)	(0.970)	(0.965)
DDD	0.530	0.039	-	1.093	-1.317	-1.544	-1.600	-1.273	-1.287	-1.388	1.983	1.903
	(0.700)	(0.515)	-	(0.859)	(0.099)	(0.066)	(0.060)	(0.106)	(0.104)	(0.087)	(0.972)	(0.967)
VAR(4)	-0.591	-1.073	-1.093	-	-1.638	**-1.836**	**-1.785**	-1.533	-1.552	-1.594	1.032	1.112
	(0.279)	(0.146)	(0.141)	-	(0.056)	**(0.038)**	**(0.042)**	(0.068)	(0.065)	(0.060)	(0.845)	(0.863)
GETS	1.465	1.331	1.317	1.638	-	**-1.849**	**-1.737**	-0.246	-0.328	-0.941	2.208	2.137
	(0.924)	(0.904)	(0.901)	(0.944)	-	**(0.037)**	**(0.046)**	(0.404)	(0.373)	(0.177)	(0.983)	(0.980)
GETS-IIS	1.658	1.563	1.544	1.836	1.849	-	-1.137	0.357	0.318	-0.416	2.413	2.348
	(0.946)	(0.936)	(0.934)	(0.962)	(0.963)	-	(0.132)	(0.638)	(0.624)	(0.340)	(0.989)	(0.987)
GETS-SIS	1.674	1.618	1.600	1.785	1.737	1.137	-	1.385	1.381	0.626	2.261	2.203
	(0.948)	(0.942)	(0.940)	(0.958)	(0.954)	(0.868)	-	(0.912)	(0.911)	(0.732)	(0.985)	(0.982)
GETS-DDD	1.399	1.281	1.273	1.533	0.246	-0.357	-1.385	-	-0.319	-1.550	2.072	1.994
	(0.914)	(0.895)	(0.894)	(0.932)	(0.596)	(0.362)	(0.088)	-	(0.376)	(0.066)	(0.977)	(0.972)
GETS-IIS-DDD	1.416	1.296	1.287	1.552	0.328	-0.318	-1.381	0.319	-	-1.431	2.098	2.024
	(0.917)	(0.898)	(0.896)	(0.935)	(0.627)	(0.376)	(0.089)	(0.624)	-	(0.081)	(0.978)	(0.974)
GETS-SIS-DDD	1.487	1.399	1.388	1.594	0.941	0.416	-0.626	1.550	1.431	-	2.066	2.002
	(0.926)	(0.914)	(0.913)	(0.940)	(0.823)	(0.660)	(0.268)	(0.934)	(0.919)	-	(0.976)	(0.973)
Ridge, CV	-1.340	**-1.960**	**-1.983**	-1.032	**-2.208**	**-2.413**	**-2.261**	**-2.072**	**-2.098**	**-2.066**	-	-0.207
	(0.095)	**(0.030)**	**(0.028)**	(0.155)	**(0.017)**	**(0.011)**	**(0.015)**	**(0.023)**	**(0.022)**	**(0.024)**	-	(0.419)
Lasso, CV	-1.466	**-1.877**	**-1.903**	-1.112	**-2.137**	**-2.348**	**-2.203**	**-1.994**	**-2.024**	**-2.002**	0.207	-
	(0.076)	**(0.035)**	**(0.033)**	(0.137)	**(0.020)**	**(0.013)**	**(0.018)**	**(0.028)**	**(0.026)**	**(0.027)**	(0.581)	-
ELNET, CV	-1.505	**-2.012**	**-2.039**	-1.204	**-2.202**	**-2.409**	**-2.252**	**-2.054**	**-2.081**	**-2.051**	-0.433	-1.043
	(0.071)	**(0.026)**	**(0.025)**	(0.119)	**(0.018)**	**(0.011)**	**(0.016)**	**(0.024)**	**(0.023)**	**(0.024)**	(0.334)	(0.152)
Ridge, AIC	0.392	-0.008	-0.010	0.669	**-1.971**	**-2.226**	**-1.995**	**-1.754**	**-1.784**	**-1.756**	1.673	1.525
	(0.651)	(0.497)	(0.496)	(0.746)	**(0.029)**	**(0.017)**	**(0.027)**	**(0.045)**	**(0.042)**	**(0.044)**	(0.948)	(0.931)
Lasso, AIC	2.270	1.977	1.978	2.279	1.228	0.981	0.520	1.033	0.998	0.663	2.632	2.604
	(0.985)	(0.972)	(0.972)	(0.985)	(0.886)	(0.833)	(0.697)	(0.845)	(0.837)	(0.744)	(0.993)	(0.993)
ELNET, AIC	2.338	2.037	2.039	2.345	1.310	1.064	0.588	1.104	1.071	0.727	2.695	2.671
	(0.987)	(0.975)	(0.975)	(0.987)	(0.900)	(0.852)	(0.720)	(0.861)	(0.854)	(0.764)	(0.994)	(0.994)
k-NN	-0.968	**-1.859**	**-1.890**	-0.657	**-2.240**	**-2.458**	**-2.311**	**-2.108**	**-2.127**	**-2.103**	0.440	0.267
	(0.170)	**(0.036)**	**(0.034)**	(0.258)	**(0.016)**	**(0.010)**	**(0.014)**	**(0.022)**	**(0.021)**	**(0.022)**	(0.669)	(0.604)
wk-NN	-1.280	**-2.173**	**-2.208**	-0.928	**-2.250**	**-2.462**	**-2.307**	**-2.116**	**-2.136**	**-2.104**	0.119	-0.031
	(0.105)	**(0.019)**	**(0.017)**	(0.180)	**(0.016)**	**(0.010)**	**(0.014)**	**(0.021)**	**(0.020)**	**(0.022)**	(0.547)	(0.488)
RF	1.177	-0.128	-0.132	0.937	-1.298	-1.490	-1.557	-1.249	-1.267	-1.367	1.432	1.555
	(0.876)	(0.449)	(0.448)	(0.822)	(0.102)	(0.073)	(0.065)	(0.111)	(0.107)	(0.091)	(0.919)	(0.935)
FFNN	-0.018	-0.474	-0.478	0.303	-1.611	**-1.823**	**-1.809**	-1.538	-1.566	-1.622	1.838	1.585
	(0.493)	(0.320)	(0.318)	(0.618)	(0.059)	**(0.039)**	**(0.040)**	(0.067)	(0.064)	(0.057)	(0.962)	(0.938)
RNN	3.562	1.587	1.597	3.074	-0.275	-0.482	-0.709	-0.323	-0.345	-0.548	3.176	3.349
	(0.999)	(0.939)	(0.940)	(0.998)	(0.393)	(0.317)	(0.242)	(0.374)	(0.366)	(0.294)	(0.998)	(0.999)
SVR-LIN	-1.687	**-2.164**	**-2.214**	-1.384	**-2.151**	**-2.363**	**-2.200**	**-2.018**	**-2.047**	**-2.012**	-0.567	-0.747
	(0.051)	**(0.019)**	**(0.017)**	(0.088)	**(0.020)**	**(0.012)**	**(0.018)**	**(0.026)**	**(0.025)**	**(0.027)**	(0.287)	(0.230)
SVR-POLY	-1.404	**-1.824**	**-1.834**	-0.874	**-2.193**	**-2.403**	**-2.280**	**-2.093**	**-2.122**	**-2.097**	0.257	0.111
	(0.085)	**(0.039)**	**(0.038)**	(0.195)	**(0.018)**	**(0.011)**	**(0.015)**	**(0.022)**	**(0.021)**	**(0.022)**	(0.600)	(0.544)
SVR-RBF	-0.801	-1.150	-1.156	-0.136	**-1.909**	**-2.124**	**-2.056**	**-1.813**	**-1.836**	**-1.857**	1.503	1.466
	(0.215)	(0.130)	(0.128)	(0.446)	**(0.033)**	**(0.021)**	**(0.024)**	**(0.040)**	**(0.038)**	**(0.036)**	(0.928)	(0.924)
SVR-ANOVA	-1.379	**-1.822**	**-1.843**	-0.811	**-2.025**	**-2.240**	**-2.135**	**-1.916**	**-1.945**	**-1.941**	0.608	0.554
	(0.089)	**(0.039)**	**(0.037)**	(0.212)	**(0.026)**	**(0.016)**	**(0.020)**	**(0.032)**	**(0.030)**	**(0.031)**	(0.726)	(0.708)
AR+SVR-POLY	-1.659	**-2.365**	**-2.414**	-1.603	**-2.535**	**-2.743**	**-2.456**	**-2.325**	**-2.350**	**-2.251**	-1.309	-1.223
	(0.054)	**(0.012)**	**(0.011)**	(0.060)	**(0.008)**	**(0.005)**	**(0.010)**	**(0.013)**	**(0.013)**	**(0.016)**	(0.100)	(0.115)
AR+SVR-RBF	-1.481	**-1.948**	**-1.987**	-1.293	**-2.520**	**-2.729**	**-2.417**	**-2.291**	**-2.315**	**-2.207**	-0.570	-0.603
	(0.074)	**(0.030)**	**(0.028)**	(0.103)	**(0.009)**	**(0.005)**	**(0.011)**	**(0.014)**	**(0.014)**	**(0.017)**	(0.286)	(0.275)
AR+SVR-ANOVA	**-1.911**	**-2.549**	**-2.613**	**-1.951**	**-2.528**	**-2.732**	**-2.443**	**-2.317**	**-2.341**	**-2.240**	-1.541	-1.529
	(0.033)	**(0.008)**	**(0.007)**	**(0.030)**	**(0.008)**	**(0.005)**	**(0.010)**	**(0.014)**	**(0.013)**	**(0.016)**	(0.067)	(0.068)
AR+FFNN	-1.100	-1.648	-1.672	-0.930	**-2.272**	**-2.485**	**-2.270**	**-2.095**	**-2.124**	**-2.071**	-0.338	-0.366
	(0.140)	(0.055)	(0.052)	(0.180)	**(0.015)**	**(0.009)**	**(0.015)**	**(0.022)**	**(0.021)**	**(0.023)**	(0.369)	(0.358)
AR+RNN	-0.321	-0.701	-0.713	-0.058	**-1.775**	**-1.975**	**-1.863**	-1.681	**-1.702**	**-1.706**	0.771	0.681
	(0.375)	(0.244)	(0.241)	(0.477)	**(0.043)**	**(0.029)**	**(0.036)**	(0.051)	**(0.049)**	**(0.049)**	(0.777)	(0.749)
Ave. BM	-0.849	**-2.257**	**-2.344**	-0.413	**-1.774**	**-1.982**	**-1.932**	-1.693	**-1.709**	**-1.740**	0.910	0.856
	(0.201)	**(0.016)**	**(0.013)**	(0.341)	**(0.043)**	**(0.028)**	**(0.031)**	(0.050)	**(0.049)**	**(0.046)**	(0.815)	(0.801)
Ave. Linear	0.634	0.363	0.359	0.851	**-2.543**	**-2.869**	**-2.533**	**-2.294**	**-2.357**	**-2.217**	1.714	1.585
	(0.735)	(0.641)	(0.639)	(0.799)	**(0.008)**	**(0.004)**	**(0.008)**	**(0.014)**	**(0.012)**	**(0.017)**	(0.952)	(0.938)
Ave. Local	-1.348	**-1.879**	**-1.917**	-0.756	**-2.082**	**-2.290**	**-2.178**	**-1.960**	**-1.979**	**-1.974**	0.807	0.713
	(0.094)	**(0.035)**	**(0.032)**	(0.228)	**(0.023)**	**(0.014)**	**(0.019)**	**(0.030)**	**(0.028)**	**(0.029)**	(0.787)	(0.759)
Ave. Non-linear	-1.625	**-1.822**	**-1.851**	-0.956	**-2.060**	**-2.267**	**-2.151**	**-1.959**	**-1.986**	**-1.971**	0.236	0.132
	(0.057)	**(0.039)**	**(0.037)**	(0.173)	**(0.024)**	**(0.015)**	**(0.020)**	**(0.030)**	**(0.028)**	**(0.029)**	(0.593)	(0.552)
Ave. AR+	-1.618	**-2.153**	**-2.192**	-1.513	**-2.538**	**-2.744**	**-2.444**	**-2.318**	**-2.344**	**-2.241**	-1.190	-1.144
	(0.058)	**(0.020)**	**(0.018)**	(0.070)	**(0.008)**	**(0.005)**	**(0.010)**	**(0.014)**	**(0.013)**	**(0.016)**	(0.121)	(0.131)
Tot. Ave.	-1.010	**-1.779**	**-1.786**	-0.725	**-2.480**	**-2.710**	**-2.503**	**-2.337**	**-2.372**	**-2.298**	0.097	-0.007
	(0.160)	**(0.042)**	**(0.042)**	(0.237)	**(0.009)**	**(0.005)**	**(0.009)**	**(0.013)**	**(0.012)**	**(0.014)**	(0.538)	(0.497)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.14: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 0$. $N = 31$. Computed at origin T.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	1.505	-0.392	**-2.270**	**-2.338**	0.968	1.280	-1.177	0.018	**-3.562**	1.687	1.404	0.801
	(0.929)	(0.349)	**(0.015)**	**(0.013)**	(0.830)	(0.895)	(0.124)	(0.507)	**(0.001)**	(0.949)	(0.915)	(0.785)
RW	2.012	0.008	**-1.977**	**-2.037**	1.859	2.173	0.128	0.474	-1.587	2.164	1.824	1.150
	(0.974)	(0.503)	**(0.028)**	**(0.025)**	(0.964)	(0.981)	(0.551)	(0.680)	(0.061)	(0.981)	(0.961)	(0.870)
DDD	2.039	0.010	**-1.978**	**-2.039**	1.890	2.208	0.132	0.478	-1.597	2.214	1.834	1.156
	(0.975)	(0.504)	**(0.028)**	**(0.025)**	(0.966)	(0.983)	(0.552)	(0.682)	(0.060)	(0.983)	(0.962)	(0.872)
VAR(4)	1.204	-0.669	**-2.279**	**-2.345**	0.657	0.928	-0.937	-0.303	**-3.074**	1.384	0.874	0.136
	(0.881)	(0.254)	**(0.015)**	**(0.013)**	(0.742)	(0.820)	(0.178)	(0.382)	**(0.002)**	(0.912)	(0.805)	(0.554)
GETS	2.202	1.971	-1.228	-1.310	2.240	2.250	1.298	1.611	0.275	2.151	2.193	1.909
	(0.982)	(0.971)	(0.114)	(0.100)	(0.984)	(0.984)	(0.898)	(0.941)	(0.607)	(0.980)	(0.982)	(0.967)
GETS-IIS	2.409	2.226	-0.981	-1.064	2.458	2.462	1.490	1.823	0.482	2.363	2.403	2.124
	(0.989)	(0.983)	(0.167)	(0.148)	(0.990)	(0.990)	(0.927)	(0.961)	(0.683)	(0.988)	(0.989)	(0.979)
GETS-SIS	2.252	1.995	-0.520	-0.588	2.311	2.307	1.557	1.809	0.709	2.200	2.280	2.056
	(0.984)	(0.973)	(0.303)	(0.280)	(0.986)	(0.986)	(0.935)	(0.960)	(0.758)	(0.982)	(0.985)	(0.976)
GETS-DDD	2.054	1.754	-1.033	-1.104	2.108	2.116	1.249	1.538	0.323	2.018	2.093	1.813
	(0.976)	(0.955)	(0.155)	(0.139)	(0.978)	(0.979)	(0.889)	(0.933)	(0.626)	(0.974)	(0.978)	(0.960)
GETS-IIS-DDD	2.081	1.784	-0.998	-1.071	2.127	2.136	1.267	1.566	0.345	2.047	2.122	1.836
	(0.977)	(0.958)	(0.163)	(0.146)	(0.979)	(0.980)	(0.893)	(0.936)	(0.634)	(0.975)	(0.979)	(0.962)
GETS-SIS-DDD	2.051	1.756	-0.663	-0.727	2.103	2.104	1.367	1.622	0.548	2.012	2.097	1.857
	(0.976)	(0.956)	(0.256)	(0.236)	(0.978)	(0.978)	(0.909)	(0.943)	(0.706)	(0.973)	(0.978)	(0.964)
Ridge, CV	0.433	-1.673	**-2.632**	**-2.695**	-0.440	-0.119	-1.432	**-1.838**	**-3.176**	0.567	-0.257	-1.503
	(0.666)	(0.052)	**(0.007)**	**(0.006)**	(0.331)	(0.453)	(0.081)	**(0.038)**	**(0.002)**	(0.713)	(0.400)	(0.072)
Lasso, CV	1.043	-1.525	**-2.604**	**-2.671**	-0.267	0.031	-1.555	-1.585	**-3.349**	0.747	-0.111	-1.466
	(0.848)	(0.069)	**(0.007)**	**(0.006)**	(0.396)	(0.512)	(0.065)	(0.062)	**(0.001)**	(0.770)	(0.456)	(0.076)
ELNET, CV	-	-1.659	**-2.656**	**-2.720**	-0.547	-0.304	-1.578	**-1.771**	**-3.314**	0.363	-0.413	-1.584
	-	(0.054)	**(0.006)**	**(0.005)**	(0.294)	(0.381)	(0.062)	**(0.043)**	**(0.001)**	(0.640)	(0.341)	(0.062)
Ridge, AIC	1.659	-	**-2.517**	**-2.603**	1.520	1.669	0.095	0.520	-1.583	1.793	1.500	0.946
	(0.946)	-	**(0.009)**	**(0.007)**	(0.931)	(0.947)	(0.537)	(0.697)	(0.062)	(0.959)	(0.928)	(0.824)
Lasso, AIC	2.656	2.517	-	-0.734	2.717	2.712	2.133	2.226	1.169	2.653	2.588	2.459
	(0.994)	(0.991)	-	(0.234)	(0.995)	(0.995)	(0.980)	(0.983)	(0.874)	(0.994)	(0.993)	(0.990)
ELNET, AIC	2.720	2.603	0.734	-	2.785	2.780	2.201	2.290	1.237	2.724	2.654	2.527
	(0.995)	(0.993)	(0.766)	-	(0.995)	(0.995)	(0.982)	(0.986)	(0.887)	(0.995)	(0.994)	(0.992)
k-NN	0.547	-1.520	**-2.717**	**-2.785**	-	0.700	-1.118	-1.292	**-2.663**	0.624	0.178	-0.874
	(0.706)	(0.069)	**(0.005)**	**(0.005)**	-	(0.755)	(0.136)	(0.103)	**(0.006)**	(0.732)	(0.570)	(0.194)
wk-NN	0.304	-1.669	**-2.712**	**-2.780**	-0.700	-	-1.372	-1.525	**-3.041**	0.507	-0.128	-1.447
	(0.619)	(0.053)	**(0.005)**	**(0.005)**	(0.245)	-	(0.090)	(0.069)	**(0.002)**	(0.692)	(0.449)	(0.079)
RF	1.578	-0.095	**-2.133**	**-2.201**	1.118	1.372	-	0.304	**-2.876**	1.664	1.556	1.118
	(0.938)	(0.463)	**(0.020)**	**(0.018)**	(0.864)	(0.910)	-	(0.618)	**(0.004)**	(0.947)	(0.935)	(0.864)
FFNN	1.771	-0.520	**-2.226**	**-2.290**	1.292	1.525	-0.304	-	**-2.034**	1.931	1.503	0.590
	(0.957)	(0.303)	**(0.017)**	**(0.014)**	(0.897)	(0.931)	(0.382)	-	**(0.025)**	(0.969)	(0.929)	(0.720)
RNN	3.314	1.583	-1.169	-1.237	2.663	3.041	2.876	2.034	-	3.610	3.394	3.211
	(0.999)	(0.938)	(0.126)	(0.113)	(0.994)	(0.998)	(0.996)	(0.975)	-	(0.999)	(0.999)	(0.998)
SVR-LIN	-0.363	**-1.793**	**-2.653**	**-2.724**	-0.624	-0.507	-1.664	**-1.931**	**-3.610**	-	-0.623	-1.693
	(0.360)	**(0.041)**	**(0.006)**	**(0.005)**	(0.268)	(0.308)	(0.053)	**(0.031)**	**(0.001)**	-	(0.269)	(0.050)
SVR-POLY	0.413	-1.500	**-2.588**	**-2.654**	-0.178	0.128	-1.556	-1.503	**-3.394**	0.623	-	**-2.226**
	(0.659)	(0.072)	**(0.007)**	**(0.006)**	(0.430)	(0.551)	(0.065)	(0.071)	**(0.001)**	(0.731)	-	**(0.017)**
SVR-RBF	1.584	-0.946	**-2.459**	**-2.527**	0.874	1.447	-1.118	-0.590	**-3.211**	1.693	2.226	-
	(0.938)	(0.176)	**(0.010)**	**(0.008)**	(0.806)	(0.921)	(0.136)	(0.280)	**(0.002)**	(0.950)	(0.983)	-
SVR-ANOVA	0.760	-1.293	**-2.526**	**-2.597**	0.116	0.459	-1.524	-1.183	**-3.430**	1.320	0.571	-1.284
	(0.773)	(0.103)	**(0.008)**	**(0.007)**	(0.546)	(0.675)	(0.069)	(0.123)	**(0.001)**	(0.902)	(0.714)	(0.104)
AR+SVR-POLY	-1.107	**-2.634**	**-2.892**	**-2.965**	-1.474	-1.317	-1.655	**-2.075**	**-3.405**	-0.806	-0.995	-1.691
	(0.138)	**(0.007)**	**(0.003)**	**(0.003)**	(0.075)	(0.099)	(0.054)	**(0.023)**	**(0.001)**	(0.213)	(0.164)	(0.050)
AR+SVR-RBF	-0.448	**-2.822**	**-2.911**	**-2.988**	-0.790	-0.629	-1.510	-1.609	**-3.450**	-0.250	-0.555	-1.335
	(0.328)	**(0.004)**	**(0.003)**	**(0.003)**	(0.218)	(0.267)	(0.071)	(0.059)	**(0.001)**	(0.402)	(0.291)	(0.096)
AR+SVR-ANOVA	-1.420	**-2.739**	**-2.927**	**-2.999**	-1.596	-1.530	**-1.836**	**-2.202**	**-3.680**	-1.244	-1.195	**-1.876**
	(0.083)	**(0.005)**	**(0.003)**	**(0.003)**	(0.060)	(0.068)	**(0.038)**	**(0.018)**	**(0.000)**	(0.111)	(0.121)	**(0.035)**
AR+FFNN	-0.209	**-2.037**	**-2.735**	**-2.802**	-0.572	-0.347	-1.201	**-2.068**	**-2.788**	-0.008	-0.345	-0.999
	(0.418)	**(0.025)**	**(0.005)**	**(0.004)**	(0.286)	(0.366)	(0.119)	**(0.024)**	**(0.004)**	(0.497)	(0.366)	(0.163)
AR+RNN	0.813	-1.014	**-2.428**	**-2.503**	0.573	0.721	-0.518	-0.449	**-2.172**	1.001	0.596	0.029
	(0.789)	(0.159)	**(0.011)**	**(0.009)**	(0.715)	(0.762)	(0.304)	(0.328)	**(0.019)**	(0.838)	(0.722)	(0.512)
Ave. BM	1.000	-0.882	**-2.332**	**-2.395**	0.557	0.937	-1.044	-0.560	**-3.014**	1.321	0.786	-0.210
	(0.838)	(0.192)	**(0.013)**	**(0.011)**	(0.709)	(0.822)	(0.152)	(0.290)	**(0.003)**	(0.902)	(0.781)	(0.418)
Ave. Linear	1.689	0.673	**-2.276**	**-2.363**	1.770	1.796	0.394	0.783	-0.902	1.669	1.678	1.181
	(0.949)	(0.747)	**(0.015)**	**(0.012)**	(0.957)	(0.959)	(0.652)	(0.780)	(0.187)	(0.947)	(0.948)	(0.877)
Ave. Local	1.034	-1.351	**-2.652**	**-2.721**	0.262	0.998	-1.456	-1.103	**-3.229**	1.076	0.581	-1.333
	(0.845)	(0.093)	**(0.006)**	**(0.005)**	(0.603)	(0.837)	(0.078)	(0.139)	**(0.001)**	(0.855)	(0.717)	(0.096)
Ave. Non-linear	0.397	-1.476	**-2.555**	**-2.623**	-0.133	0.127	-1.662	-1.538	**-3.760**	0.910	0.035	**-2.076**
	(0.653)	(0.075)	**(0.008)**	**(0.007)**	(0.447)	(0.550)	(0.053)	(0.067)	**(0.000)**	(0.815)	(0.514)	**(0.023)**
Ave. AR+	-1.035	**-2.837**	**-2.927**	**-3.001**	-1.353	-1.176	-1.618	**-2.231**	**-3.395**	-0.821	-0.957	-1.621
	(0.154)	**(0.004)**	**(0.003)**	**(0.003)**	(0.093)	(0.124)	(0.058)	**(0.017)**	**(0.001)**	(0.209)	(0.173)	(0.058)
Tot. Ave.	0.222	**-1.798**	**-2.723**	**-2.792**	-0.375	0.019	-1.179	-1.569	**-2.737**	0.379	-0.091	-1.064
	(0.587)	**(0.041)**	**(0.005)**	**(0.004)**	(0.355)	(0.508)	(0.124)	(0.063)	**(0.005)**	(0.646)	(0.464)	(0.148)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.15: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 0$. $N = 31$. Computed at origin T.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	1.379	1.659	1.481	1.911	1.100	0.321	0.849	-0.634	1.348	1.625	1.618	1.010
	(0.911)	(0.946)	(0.926)	(0.967)	(0.860)	(0.625)	(0.799)	(0.265)	(0.906)	(0.943)	(0.942)	(0.840)
RW	1.822	2.365	1.948	2.549	1.648	0.701	2.257	-0.363	1.879	1.822	2.153	1.779
	(0.961)	(0.988)	(0.970)	(0.992)	(0.945)	(0.756)	(0.984)	(0.359)	(0.965)	(0.961)	(0.980)	(0.958)
DDD	1.843	2.414	1.987	2.613	1.672	0.713	2.344	-0.359	1.917	1.851	2.192	1.786
	(0.963)	(0.989)	(0.972)	(0.993)	(0.948)	(0.759)	(0.987)	(0.361)	(0.968)	(0.963)	(0.982)	(0.958)
VAR(4)	0.811	1.603	1.293	1.951	0.930	0.058	0.413	-0.851	0.756	0.956	1.513	0.725
	(0.788)	(0.940)	(0.897)	(0.970)	(0.820)	(0.523)	(0.659)	(0.201)	(0.772)	(0.827)	(0.930)	(0.763)
GETS	2.025	2.535	2.520	2.528	2.272	1.775	1.774	2.543	2.082	2.060	2.538	2.480
	(0.974)	(0.992)	(0.991)	(0.992)	(0.985)	(0.957)	(0.957)	(0.992)	(0.977)	(0.976)	(0.992)	(0.991)
GETS-IIS	2.240	2.743	2.729	2.732	2.485	1.975	1.982	2.869	2.290	2.267	2.744	2.710
	(0.984)	(0.995)	(0.995)	(0.995)	(0.991)	(0.971)	(0.972)	(0.996)	(0.986)	(0.985)	(0.995)	(0.995)
GETS-SIS	2.135	2.456	2.417	2.443	2.270	1.863	1.932	2.533	2.178	2.151	2.444	2.503
	(0.980)	(0.990)	(0.989)	(0.990)	(0.985)	(0.964)	(0.969)	(0.992)	(0.981)	(0.980)	(0.990)	(0.991)
GETS-DDD	1.916	2.325	2.291	2.317	2.095	1.681	1.693	2.294	1.960	1.959	2.318	2.337
	(0.968)	(0.987)	(0.986)	(0.986)	(0.978)	(0.949)	(0.950)	(0.986)	(0.970)	(0.970)	(0.986)	(0.987)
GETS-IIS-DDD	1.945	2.350	2.315	2.341	2.124	1.702	1.709	2.357	1.979	1.986	2.344	2.372
	(0.970)	(0.987)	(0.986)	(0.987)	(0.979)	(0.951)	(0.951)	(0.988)	(0.972)	(0.972)	(0.987)	(0.988)
GETS-SIS-DDD	1.941	2.251	2.207	2.240	2.071	1.706	1.740	2.217	1.974	1.971	2.241	2.298
	(0.969)	(0.984)	(0.983)	(0.984)	(0.977)	(0.951)	(0.954)	(0.983)	(0.971)	(0.971)	(0.984)	(0.986)
Ridge, CV	-0.608	1.309	0.570	1.541	0.338	-0.771	-0.910	**-1.714**	-0.807	-0.236	1.190	-0.097
	(0.274)	(0.900)	(0.714)	(0.933)	(0.631)	(0.223)	(0.185)	**(0.048)**	(0.213)	(0.407)	(0.879)	(0.462)
Lasso, CV	-0.554	1.223	0.603	1.529	0.366	-0.681	-0.856	-1.585	-0.713	-0.132	1.144	0.007
	(0.292)	(0.885)	(0.725)	(0.932)	(0.642)	(0.251)	(0.199)	(0.062)	(0.241)	(0.448)	(0.869)	(0.503)
ELNET, CV	-0.760	1.107	0.448	1.420	0.209	-0.813	-1.000	-1.689	-1.034	-0.397	1.035	-0.222
	(0.227)	(0.862)	(0.672)	(0.917)	(0.582)	(0.211)	(0.162)	(0.051)	(0.155)	(0.347)	(0.846)	(0.413)
Ridge, AIC	1.293	2.634	2.822	2.739	2.037	1.014	0.882	-0.673	1.351	1.476	2.837	1.798
	(0.897)	(0.993)	(0.996)	(0.995)	(0.975)	(0.841)	(0.808)	(0.253)	(0.907)	(0.925)	(0.996)	(0.959)
Lasso, AIC	2.526	2.892	2.911	2.927	2.735	2.428	2.332	2.276	2.652	2.555	2.927	2.723
	(0.992)	(0.997)	(0.997)	(0.997)	(0.995)	(0.989)	(0.987)	(0.985)	(0.994)	(0.992)	(0.997)	(0.995)
ELNET, AIC	2.597	2.965	2.988	2.999	2.802	2.503	2.395	2.363	2.721	2.623	3.001	2.792
	(0.993)	(0.997)	(0.997)	(0.997)	(0.996)	(0.991)	(0.989)	(0.988)	(0.995)	(0.993)	(0.997)	(0.996)
k-NN	-0.116	1.474	0.790	1.596	0.572	-0.573	-0.557	**-1.770**	-0.262	0.133	1.353	0.375
	(0.454)	(0.925)	(0.782)	(0.940)	(0.714)	(0.285)	(0.291)	**(0.043)**	(0.397)	(0.553)	(0.907)	(0.645)
wk-NN	-0.459	1.317	0.629	1.530	0.347	-0.721	-0.937	**-1.796**	-0.998	-0.127	1.176	-0.019
	(0.325)	(0.901)	(0.733)	(0.932)	(0.634)	(0.238)	(0.178)	**(0.041)**	(0.163)	(0.450)	(0.876)	(0.492)
RF	1.524	1.655	1.510	1.836	1.201	0.518	1.044	-0.394	1.456	1.662	1.618	1.179
	(0.931)	(0.946)	(0.929)	(0.962)	(0.881)	(0.696)	(0.848)	(0.348)	(0.922)	(0.947)	(0.942)	(0.876)
FFNN	1.183	2.075	1.609	2.202	2.068	0.449	0.560	-0.783	1.103	1.538	2.231	1.569
	(0.877)	(0.977)	(0.941)	(0.982)	(0.976)	(0.672)	(0.710)	(0.220)	(0.861)	(0.933)	(0.983)	(0.937)
RNN	3.430	3.405	3.450	3.680	2.788	2.172	3.014	0.902	3.229	3.760	3.395	2.737
	(0.999)	(0.999)	(0.999)	(1.000)	(0.996)	(0.981)	(0.997)	(0.813)	(0.999)	(1.000)	(0.999)	(0.995)
SVR-LIN	-1.320	0.806	0.250	1.244	0.008	-1.001	-1.321	-1.669	-1.076	-0.910	0.821	-0.379
	(0.098)	(0.787)	(0.598)	(0.889)	(0.503)	(0.162)	(0.098)	(0.053)	(0.145)	(0.185)	(0.791)	(0.354)
SVR-POLY	-0.571	0.995	0.555	1.195	0.345	-0.596	-0.786	-1.678	-0.581	-0.035	0.957	0.091
	(0.286)	(0.836)	(0.709)	(0.879)	(0.634)	(0.278)	(0.219)	(0.052)	(0.283)	(0.486)	(0.827)	(0.536)
SVR-RBF	1.284	1.691	1.335	1.876	0.999	-0.029	0.210	-1.181	1.333	2.076	1.621	1.064
	(0.896)	(0.950)	(0.904)	(0.965)	(0.837)	(0.488)	(0.582)	(0.123)	(0.904)	(0.977)	(0.942)	(0.852)
SVR-ANOVA	-	1.194	0.752	1.441	0.520	-0.436	-0.642	-1.427	-0.077	0.702	1.126	0.347
	-	(0.879)	(0.771)	(0.920)	(0.697)	(0.333)	(0.263)	(0.082)	(0.470)	(0.756)	(0.866)	(0.635)
AR+SVR-POLY	-1.194	-	-0.926	1.340	-0.901	**-1.722**	-1.494	**-2.192**	-1.499	-1.005	0.339	-1.079
	(0.121)	-	(0.181)	(0.905)	(0.187)	**(0.047)**	(0.073)	**(0.018)**	(0.072)	(0.161)	(0.631)	(0.144)
AR+SVR-RBF	-0.752	0.926	-	1.881	-0.252	-1.425	-1.105	**-2.091**	-0.954	-0.584	1.135	-0.535
	(0.229)	(0.819)	-	(0.965)	(0.401)	(0.082)	(0.139)	**(0.022)**	(0.174)	(0.282)	(0.867)	(0.298)
AR+SVR-ANOVA	-1.441	-1.340	**-1.881**	-	-1.236	**-2.031**	**-1.807**	**-2.178**	**-1.749**	-1.287	-0.676	-1.197
	(0.080)	(0.095)	**(0.035)**	-	(0.113)	**(0.025)**	**(0.040)**	**(0.019)**	**(0.045)**	(0.104)	(0.252)	(0.120)
AR+FFNN	-0.520	0.901	0.252	1.236	-	-1.451	-0.759	**-1.785**	-0.603	-0.364	1.341	-0.357
	(0.303)	(0.813)	(0.599)	(0.887)	-	(0.078)	(0.227)	**(0.042)**	(0.276)	(0.359)	(0.905)	(0.362)
AR+RNN	0.436	1.722	1.425	2.031	1.451	-	0.127	-1.015	0.437	0.618	2.261	0.675
	(0.667)	(0.953)	(0.918)	(0.975)	(0.922)	-	(0.550)	(0.159)	(0.667)	(0.730)	(0.985)	(0.748)
Ave. BM	0.642	1.494	1.105	1.807	0.759	-0.127	-	-1.080	0.604	0.860	1.357	0.634
	(0.737)	(0.927)	(0.861)	(0.960)	(0.773)	(0.450)	-	(0.144)	(0.725)	(0.802)	(0.908)	(0.735)
Ave. Linear	1.427	2.192	2.091	2.178	1.785	1.015	1.080	-	1.500	1.508	2.178	2.167
	(0.918)	(0.982)	(0.978)	(0.981)	(0.958)	(0.841)	(0.856)	-	(0.928)	(0.929)	(0.981)	(0.981)
Ave. Local	0.077	1.499	0.954	1.749	0.603	-0.437	-0.604	-1.500	-	0.500	1.357	0.445
	(0.530)	(0.928)	(0.826)	(0.955)	(0.724)	(0.333)	(0.275)	(0.072)	-	(0.690)	(0.908)	(0.670)
Ave. Non-linear	-0.702	1.005	0.584	1.287	0.364	-0.618	-0.860	-1.508	-0.500	-	1.003	0.084
	(0.244)	(0.839)	(0.718)	(0.896)	(0.641)	(0.270)	(0.198)	(0.071)	(0.310)	-	(0.838)	(0.533)
Ave. AR+	-1.126	-0.339	-1.135	0.676	-1.341	**-2.261**	-1.357	**-2.178**	-1.357	-1.003	-	-1.033
	(0.134)	(0.369)	(0.133)	(0.748)	(0.095)	**(0.015)**	(0.092)	**(0.019)**	(0.092)	(0.162)	-	(0.155)
Tot. Ave.	-0.347	1.079	0.535	1.197	0.357	-0.675	-0.634	**-2.167**	-0.445	-0.084	1.033	-
	(0.365)	(0.856)	(0.702)	(0.880)	(0.638)	(0.252)	(0.265)	**(0.019)**	(0.330)	(0.467)	(0.845)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.16: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 0$. $N = 31$. Computed one month after end of reference quarter T.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.520	-0.530	0.324	-0.766	-0.932	-0.598	-1.161	-0.937	-0.894	1.476	1.529
	-	(0.304)	(0.300)	(0.626)	(0.225)	(0.179)	(0.277)	(0.127)	(0.178)	(0.189)	(0.925)	(0.932)
RW	0.520	-	-0.039	0.843	-0.530	-0.598	-0.410	-1.260	-0.696	-0.922	2.102	2.145
	(0.696)	-	(0.485)	(0.797)	(0.300)	(0.277)	(0.342)	(0.109)	(0.246)	(0.182)	(0.978)	(0.980)
DDD	0.530	0.039	-	0.859	-0.536	-0.604	-0.405	-1.256	-0.710	-0.917	2.127	2.169
	(0.700)	(0.515)	-	(0.801)	(0.298)	(0.275)	(0.344)	(0.109)	(0.241)	(0.183)	(0.979)	(0.981)
VAR(4)	-0.324	-0.843	-0.859	-	-1.151	-1.303	-0.827	-1.451	-1.328	-1.163	1.326	1.382
	(0.374)	(0.203)	(0.199)	-	(0.129)	(0.101)	(0.207)	(0.078)	(0.097)	(0.127)	(0.903)	(0.912)
GETS	0.766	0.530	0.536	1.151	-	-0.411	0.151	-1.146	-0.482	-0.475	1.918	1.880
	(0.775)	(0.700)	(0.702)	(0.871)	-	(0.342)	(0.559)	(0.130)	(0.317)	(0.319)	(0.968)	(0.965)
GETS-IIS	0.932	0.598	0.604	1.303	0.411	-	0.260	-0.619	-0.074	-0.175	1.876	1.844
	(0.821)	(0.723)	(0.725)	(0.899)	(0.658)	-	(0.602)	(0.270)	(0.471)	(0.431)	(0.965)	(0.963)
GETS-SIS	0.598	0.410	0.405	0.827	-0.151	-0.260	-	**-1.906**	-0.315	-1.379	1.881	1.874
	(0.723)	(0.658)	(0.656)	(0.793)	(0.441)	(0.398)	-	**(0.033)**	(0.378)	(0.089)	(0.965)	(0.965)
GETS-DDD	1.161	1.260	1.256	1.451	1.146	0.619	1.906	-	0.683	1.212	2.245	2.226
	(0.873)	(0.891)	(0.891)	(0.922)	(0.870)	(0.730)	(0.967)	-	(0.750)	(0.883)	(0.984)	(0.983)
GETS-IIS-DDD	0.937	0.696	0.710	1.328	0.482	0.074	0.315	-0.683	-	-0.176	2.008	1.968
	(0.822)	(0.754)	(0.759)	(0.903)	(0.683)	(0.529)	(0.622)	(0.250)	-	(0.431)	(0.973)	(0.971)
GETS-SIS-DDD	0.894	0.922	0.917	1.163	0.475	0.175	1.379	-1.212	0.176	-	2.054	2.040
	(0.811)	(0.818)	(0.817)	(0.873)	(0.681)	(0.569)	(0.911)	(0.117)	(0.569)	-	(0.976)	(0.975)
Ridge, CV	-1.476	**-2.102**	**-2.127**	-1.326	**-1.918**	**-1.876**	**-1.881**	**-2.245**	**-2.008**	**-2.054**	-	0.069
	(0.075)	**(0.022)**	**(0.021)**	(0.097)	**(0.032)**	**(0.035)**	**(0.035)**	**(0.016)**	**(0.027)**	**(0.024)**	-	(0.527)
Lasso, CV	-1.529	**-2.145**	**-2.169**	-1.382	**-1.880**	**-1.844**	**-1.874**	**-2.226**	**-1.968**	**-2.040**	-0.069	-
	(0.068)	**(0.020)**	**(0.019)**	(0.088)	**(0.035)**	**(0.037)**	**(0.035)**	**(0.017)**	**(0.029)**	**(0.025)**	(0.473)	-
ELNET, CV	-1.489	**-2.209**	**-2.234**	-1.394	**-1.972**	**-1.908**	**-1.989**	**-2.322**	**-2.066**	**-2.144**	-0.615	-0.751
	(0.073)	**(0.017)**	**(0.016)**	(0.087)	**(0.029)**	**(0.033)**	**(0.028)**	**(0.013)**	**(0.024)**	**(0.020)**	(0.272)	(0.229)
Ridge, AIC	0.171	-0.222	-0.225	0.333	-0.800	-1.026	-0.557	-1.457	-1.049	-0.916	1.398	1.372
	(0.567)	(0.413)	(0.412)	(0.629)	(0.215)	(0.156)	(0.291)	(0.078)	(0.151)	(0.183)	(0.914)	(0.910)
Lasso, AIC	2.703	2.019	2.016	2.478	1.676	1.666	1.641	1.209	1.537	1.385	2.568	2.572
	(0.994)	(0.974)	(0.974)	(0.991)	(0.948)	(0.947)	(0.945)	(0.882)	(0.933)	(0.912)	(0.992)	(0.992)
ELNET, AIC	2.663	2.064	2.061	2.470	1.753	1.754	1.721	1.318	1.623	1.479	2.551	2.558
	(0.994)	(0.976)	(0.976)	(0.990)	(0.955)	(0.955)	(0.952)	(0.901)	(0.943)	(0.925)	(0.992)	(0.992)
k-NN	-0.024	-0.590	-0.600	0.158	-0.816	-0.873	-0.839	-1.471	-0.945	-1.177	2.357	2.304
	(0.490)	(0.280)	(0.277)	(0.562)	(0.210)	(0.195)	(0.204)	(0.076)	(0.176)	(0.124)	(0.988)	(0.986)
wk-NN	-0.674	-1.503	-1.527	-0.450	-1.425	-1.376	-1.517	**-2.018**	-1.487	**-1.775**	2.157	2.032
	(0.253)	(0.071)	(0.068)	(0.328)	(0.082)	(0.089)	(0.070)	**(0.026)**	(0.074)	**(0.043)**	(0.981)	(0.975)
RF	0.965	-0.142	-0.146	0.687	-0.455	-0.604	-0.341	-0.896	-0.597	-0.633	1.419	1.470
	(0.829)	(0.444)	(0.443)	(0.751)	(0.326)	(0.275)	(0.368)	(0.189)	(0.277)	(0.266)	(0.917)	(0.924)
FFNN	0.002	-0.493	-0.498	0.166	-0.838	-0.897	-0.844	-1.482	-0.968	-1.175	2.223	2.047
	(0.501)	(0.313)	(0.311)	(0.565)	(0.204)	(0.188)	(0.203)	(0.074)	(0.170)	(0.125)	(0.983)	(0.975)
RNN	2.971	2.394	2.389	2.816	1.925	1.854	1.926	1.438	1.751	1.660	2.818	2.839
	(0.997)	(0.989)	(0.988)	(0.996)	(0.968)	(0.963)	(0.968)	(0.920)	(0.955)	(0.947)	(0.996)	(0.996)
SVR-LIN	-1.531	**-1.989**	**-2.029**	-1.255	**-1.848**	**-1.881**	-1.648	**-2.074**	**-1.961**	**-1.848**	0.464	0.453
	(0.068)	**(0.028)**	**(0.026)**	(0.109)	**(0.037)**	**(0.035)**	(0.055)	**(0.023)**	**(0.029)**	**(0.037)**	(0.677)	(0.673)
SVR-POLY	-0.770	-1.375	-1.369	-0.515	-1.312	-1.307	-1.451	**-1.904**	-1.361	-1.666	1.554	1.676
	(0.224)	(0.090)	(0.090)	(0.305)	(0.100)	(0.100)	(0.078)	**(0.033)**	(0.092)	(0.053)	(0.935)	(0.948)
SVR-RBF	-0.678	-1.132	-1.141	-0.307	-1.188	-1.232	-1.174	**-1.719**	-1.272	-1.441	1.776	1.771
	(0.251)	(0.133)	(0.131)	(0.380)	(0.122)	(0.114)	(0.125)	**(0.048)**	(0.106)	(0.080)	(0.957)	(0.957)
SVR-ANOVA	-0.955	-1.614	-1.626	-0.696	-1.497	-1.477	-1.556	**-2.001**	-1.558	**-1.774**	1.632	1.744
	(0.174)	(0.058)	(0.057)	(0.246)	(0.072)	(0.075)	(0.065)	**(0.027)**	(0.065)	**(0.043)**	(0.944)	(0.955)
AR+SVR-POLY	**-1.719**	**-2.439**	**-2.490**	**-1.782**	**-2.611**	**-2.602**	**-2.217**	**-2.650**	**-2.938**	**-2.387**	-1.281	-1.188
	(0.048)	**(0.010)**	**(0.009)**	**(0.042)**	**(0.007)**	**(0.007)**	**(0.017)**	**(0.006)**	**(0.003)**	**(0.012)**	(0.105)	(0.122)
AR+SVR-RBF	-1.430	**-1.916**	**-1.953**	-1.393	**-2.362**	**-2.549**	**-1.840**	**-2.419**	**-2.787**	**-2.046**	-0.436	-0.404
	(0.081)	**(0.032)**	**(0.030)**	(0.087)	**(0.012)**	**(0.008)**	**(0.038)**	**(0.011)**	**(0.005)**	**(0.025)**	(0.333)	(0.345)
AR+SVR-ANOVA	**-1.937**	**-2.522**	**-2.586**	**-2.031**	**-2.731**	**-2.840**	**-2.152**	**-2.602**	**-3.168**	**-2.330**	-1.383	-1.302
	(0.031)	**(0.009)**	**(0.007)**	**(0.025)**	**(0.005)**	**(0.004)**	**(0.020)**	**(0.007)**	**(0.002)**	**(0.013)**	(0.088)	(0.101)
AR+FFNN	-0.805	-1.302	-1.313	-0.735	-1.588	-1.619	-1.554	**-2.025**	**-1.779**	**-1.787**	0.275	0.283
	(0.213)	(0.101)	(0.099)	(0.234)	(0.061)	(0.058)	(0.065)	**(0.026)**	**(0.043)**	**(0.042)**	(0.607)	(0.610)
AR+RNN	-0.470	-0.975	-0.994	-0.359	-1.454	-1.537	-1.210	**-1.720**	-1.665	-1.464	0.833	0.802
	(0.321)	(0.169)	(0.164)	(0.361)	(0.078)	(0.067)	(0.118)	**(0.048)**	(0.053)	(0.077)	(0.794)	(0.786)
Ave. BM	-0.801	**-2.157**	**-2.240**	-0.638	-1.547	-1.540	-1.266	**-1.847**	-1.659	-1.599	1.109	1.119
	(0.215)	**(0.019)**	**(0.016)**	(0.264)	(0.066)	(0.067)	(0.107)	**(0.037)**	(0.054)	(0.060)	(0.862)	(0.864)
Ave. Linear	-0.162	-0.880	-0.901	-0.006	**-1.829**	-1.574	-1.369	**-2.272**	**-1.936**	**-1.799**	1.529	1.466
	(0.436)	(0.193)	(0.187)	(0.498)	**(0.039)**	(0.063)	(0.090)	**(0.015)**	**(0.031)**	**(0.041)**	(0.932)	(0.924)
Ave. Local	-0.773	-1.145	-1.166	-0.306	-1.159	-1.224	-1.094	-1.640	-1.275	-1.374	1.881	1.962
	(0.223)	(0.130)	(0.126)	(0.381)	(0.128)	(0.115)	(0.141)	(0.056)	(0.106)	(0.090)	(0.965)	(0.971)
Ave. Non-linear	-0.762	-1.233	-1.243	-0.384	-1.229	-1.268	-1.205	**-1.710**	-1.291	-1.460	1.423	1.434
	(0.226)	(0.113)	(0.112)	(0.352)	(0.114)	(0.107)	(0.119)	**(0.049)**	(0.103)	(0.077)	(0.918)	(0.919)
Ave. AR+	-1.588	**-2.231**	**-2.272**	-1.629	**-2.508**	**-2.535**	**-2.156**	**-2.582**	**-2.855**	**-2.324**	-1.101	-1.034
	(0.061)	**(0.017)**	**(0.015)**	(0.057)	**(0.009)**	**(0.008)**	**(0.019)**	**(0.007)**	**(0.004)**	**(0.013)**	(0.140)	(0.155)
Tot. Ave.	-1.257	**-2.374**	**-2.421**	-1.301	**-2.477**	**-2.190**	**-2.539**	**-2.840**	**-2.585**	**-2.718**	-0.612	-0.561
	(0.109)	**(0.012)**	**(0.011)**	(0.101)	**(0.009)**	**(0.018)**	**(0.008)**	**(0.004)**	**(0.007)**	**(0.005)**	(0.272)	(0.290)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.17: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 0$. $N = 31$. Computed one month after end of reference quarter T.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	1.489	-0.171	**-2.703**	**-2.663**	0.024	0.674	-0.965	-0.002	**-2.971**	1.531	0.770	0.678
	(0.927)	(0.433)	**(0.006)**	**(0.006)**	(0.510)	(0.747)	(0.171)	(0.499)	**(0.003)**	(0.932)	(0.776)	(0.749)
RW	2.209	0.222	**-2.019**	**-2.064**	0.590	1.503	0.142	0.493	**-2.394**	1.989	1.375	1.132
	(0.983)	(0.587)	**(0.026)**	**(0.024)**	(0.720)	(0.929)	(0.556)	(0.687)	**(0.011)**	(0.972)	(0.910)	(0.867)
DDD	2.234	0.225	**-2.016**	**-2.061**	0.600	1.527	0.146	0.498	**-2.389**	2.029	1.369	1.141
	(0.984)	(0.588)	**(0.026)**	**(0.024)**	(0.723)	(0.932)	(0.557)	(0.689)	**(0.012)**	(0.974)	(0.910)	(0.869)
VAR(4)	1.394	-0.333	**-2.478**	**-2.470**	-0.158	0.450	-0.687	-0.166	**-2.816**	1.255	0.515	0.307
	(0.913)	(0.371)	**(0.009)**	**(0.010)**	(0.438)	(0.672)	(0.249)	(0.435)	**(0.004)**	(0.891)	(0.695)	(0.620)
GETS	1.972	0.800	-1.676	**-1.753**	0.816	1.425	0.455	0.838	**-1.925**	1.848	1.312	1.188
	(0.971)	(0.785)	(0.052)	**(0.045)**	(0.790)	(0.918)	(0.674)	(0.796)	**(0.032)**	(0.963)	(0.900)	(0.878)
GETS-IIS	1.908	1.026	-1.666	**-1.754**	0.873	1.376	0.604	0.897	**-1.854**	1.881	1.307	1.232
	(0.967)	(0.844)	(0.053)	**(0.045)**	(0.805)	(0.911)	(0.725)	(0.812)	**(0.037)**	(0.965)	(0.900)	(0.886)
GETS-SIS	1.989	0.557	-1.641	**-1.721**	0.839	1.517	0.341	0.844	**-1.926**	1.648	1.451	1.174
	(0.972)	(0.709)	(0.055)	**(0.048)**	(0.796)	(0.930)	(0.632)	(0.797)	**(0.032)**	(0.945)	(0.922)	(0.875)
GETS-DDD	2.322	1.457	-1.209	-1.318	1.471	2.018	0.896	1.482	-1.438	2.074	1.904	1.719
	(0.987)	(0.922)	(0.118)	(0.099)	(0.924)	(0.974)	(0.811)	(0.926)	(0.080)	(0.977)	(0.967)	(0.952)
GETS-IIS-DDD	2.066	1.049	-1.537	-1.623	0.945	1.487	0.597	0.968	**-1.751**	1.961	1.361	1.272
	(0.976)	(0.849)	(0.067)	(0.057)	(0.824)	(0.926)	(0.723)	(0.830)	**(0.045)**	(0.971)	(0.908)	(0.894)
GETS-SIS-DDD	2.144	0.916	-1.385	-1.479	1.177	1.775	0.633	1.175	-1.660	1.848	1.666	1.441
	(0.980)	(0.817)	(0.088)	(0.075)	(0.876)	(0.957)	(0.734)	(0.875)	(0.053)	(0.963)	(0.947)	(0.920)
Ridge, CV	0.615	-1.398	**-2.568**	**-2.551**	**-2.357**	**-2.157**	-1.419	**-2.223**	**-2.818**	-0.464	-1.554	**-1.776**
	(0.728)	(0.086)	**(0.008)**	**(0.008)**	**(0.012)**	**(0.019)**	(0.083)	**(0.017)**	**(0.004)**	(0.323)	(0.065)	**(0.043)**
Lasso, CV	0.751	-1.372	**-2.572**	**-2.558**	**-2.304**	**-2.032**	-1.470	**-2.047**	**-2.839**	-0.453	-1.676	**-1.771**
	(0.771)	(0.090)	**(0.008)**	**(0.008)**	**(0.014)**	**(0.025)**	(0.076)	**(0.025)**	**(0.004)**	(0.327)	(0.052)	**(0.043)**
ELNET, CV	-	-1.489	**-2.536**	**-2.524**	**-2.360**	**-2.120**	-1.437	**-2.260**	**-2.792**	-0.599	-1.645	**-1.701**
	-	(0.073)	**(0.008)**	**(0.008)**	**(0.012)**	**(0.021)**	(0.080)	**(0.015)**	**(0.004)**	(0.277)	(0.055)	**(0.049)**
Ridge, AIC	1.489	-	**-1.935**	**-1.983**	0.237	0.743	-0.073	0.260	**-2.007**	1.262	0.758	0.581
	(0.927)	-	**(0.031)**	**(0.028)**	(0.593)	(0.769)	(0.471)	(0.602)	**(0.027)**	(0.892)	(0.773)	(0.717)
Lasso, AIC	2.536	1.935	-	-1.376	2.255	2.424	2.839	2.134	-0.194	2.650	2.494	2.576
	(0.992)	(0.969)	-	(0.089)	(0.984)	(0.989)	(0.996)	(0.980)	(0.424)	(0.994)	(0.991)	(0.993)
ELNET, AIC	2.524	1.983	1.376	-	2.269	2.421	2.782	2.159	0.208	2.631	2.492	2.557
	(0.992)	(0.972)	(0.911)	-	(0.985)	(0.989)	(0.995)	(0.981)	(0.582)	(0.993)	(0.991)	(0.992)
k-NN	2.360	-0.237	**-2.255**	**-2.269**	-	1.408	-0.334	-0.044	**-2.479**	1.784	1.268	0.968
	(0.988)	(0.407)	**(0.016)**	**(0.015)**	-	(0.915)	(0.370)	(0.482)	**(0.009)**	(0.958)	(0.893)	(0.830)
wk-NN	2.120	-0.743	**-2.424**	**-2.421**	-1.408	-	-0.850	-0.972	**-2.705**	1.252	0.201	-0.405
	(0.979)	(0.231)	**(0.011)**	**(0.011)**	(0.085)	-	(0.201)	(0.169)	**(0.005)**	(0.890)	(0.579)	(0.344)
RF	1.437	0.073	**-2.839**	**-2.782**	0.334	0.850	-	0.259	**-3.089**	1.450	0.985	0.929
	(0.920)	(0.529)	**(0.004)**	**(0.005)**	(0.630)	(0.799)	-	(0.601)	**(0.002)**	(0.921)	(0.834)	(0.820)
FFNN	2.260	-0.260	**-2.134**	**-2.159**	0.044	0.972	-0.259	-	**-2.267**	1.682	0.993	0.620
	(0.985)	(0.398)	**(0.020)**	**(0.019)**	(0.518)	(0.831)	(0.399)	-	**(0.015)**	(0.949)	(0.836)	(0.730)
RNN	2.792	2.007	0.194	-0.208	2.479	2.705	3.089	2.267	-	2.891	2.783	2.844
	(0.996)	(0.973)	(0.576)	(0.418)	(0.991)	(0.995)	(0.998)	(0.985)	-	(0.997)	(0.995)	(0.996)
SVR-LIN	0.599	-1.262	**-2.650**	**-2.631**	**-1.784**	-1.252	-1.450	-1.682	**-2.891**	-	-0.982	-1.466
	(0.723)	(0.108)	**(0.006)**	**(0.007)**	**(0.042)**	(0.110)	(0.079)	(0.051)	**(0.003)**	-	(0.167)	(0.076)
SVR-POLY	1.645	-0.758	**-2.494**	**-2.492**	-1.268	-0.201	-0.985	-0.993	**-2.783**	0.982	-	-0.621
	(0.945)	(0.227)	**(0.009)**	**(0.009)**	(0.107)	(0.421)	(0.166)	(0.164)	**(0.005)**	(0.833)	-	(0.269)
SVR-RBF	1.701	-0.581	**-2.576**	**-2.557**	-0.968	0.405	-0.929	-0.620	**-2.844**	1.466	0.621	-
	(0.951)	(0.283)	**(0.007)**	**(0.008)**	(0.170)	(0.656)	(0.180)	(0.270)	**(0.004)**	(0.924)	(0.731)	-
SVR-ANOVA	1.681	-0.886	**-2.536**	**-2.537**	-1.476	-0.602	-1.096	-1.177	**-2.800**	1.123	-0.415	-0.913
	(0.949)	(0.191)	**(0.008)**	**(0.008)**	(0.075)	(0.276)	(0.141)	(0.124)	**(0.004)**	(0.865)	(0.341)	(0.184)
AR+SVR-POLY	-1.162	**-2.427**	**-2.544**	**-2.532**	**-2.224**	**-1.929**	-1.590	**-2.534**	**-2.767**	-1.370	-1.568	**-1.730**
	(0.127)	**(0.011)**	**(0.008)**	**(0.008)**	**(0.017)**	**(0.031)**	(0.061)	**(0.008)**	**(0.005)**	(0.090)	(0.064)	**(0.047)**
AR+SVR-RBF	-0.301	**-2.384**	**-2.480**	**-2.475**	-1.672	-1.219	-1.383	**-1.825**	**-2.687**	-0.626	-1.014	-1.251
	(0.383)	**(0.012)**	**(0.009)**	**(0.009)**	(0.052)	(0.116)	(0.088)	**(0.039)**	**(0.006)**	(0.268)	(0.159)	(0.110)
AR+SVR-ANOVA	-1.245	**-2.493**	**-2.615**	**-2.596**	**-2.207**	**-1.927**	**-1.739**	**-2.438**	**-2.839**	-1.600	-1.587	**-1.817**
	(0.111)	**(0.009)**	**(0.007)**	**(0.007)**	**(0.017)**	**(0.032)**	**(0.046)**	**(0.010)**	**(0.004)**	(0.060)	(0.061)	**(0.039)**
AR+FFNN	0.420	-1.346	**-2.250**	**-2.266**	-1.132	-0.553	-0.903	-1.676	**-2.436**	0.065	-0.470	-0.619
	(0.661)	(0.094)	**(0.016)**	**(0.015)**	(0.133)	(0.292)	(0.187)	(0.052)	**(0.010)**	(0.526)	(0.321)	(0.270)
AR+RNN	0.973	-0.829	**-2.123**	**-2.147**	-0.556	-0.034	-0.616	-0.719	**-2.283**	0.611	0.030	-0.153
	(0.831)	(0.207)	**(0.021)**	**(0.020)**	(0.291)	(0.487)	(0.271)	(0.239)	**(0.015)**	(0.727)	(0.512)	(0.440)
Ave. BM	1.164	-0.627	**-2.502**	**-2.498**	-0.670	0.012	-0.937	-0.574	**-2.931**	1.021	0.101	-0.212
	(0.873)	(0.268)	**(0.009)**	**(0.009)**	(0.254)	(0.505)	(0.178)	(0.285)	**(0.003)**	(0.843)	(0.540)	(0.417)
Ave. Linear	1.679	-0.584	**-2.085**	**-2.120**	-0.198	0.542	-0.378	-0.265	**-2.297**	1.266	0.508	0.273
	(0.948)	(0.282)	**(0.023)**	**(0.021)**	(0.422)	(0.704)	(0.354)	(0.396)	**(0.014)**	(0.893)	(0.693)	(0.607)
Ave. Local	1.830	-0.549	**-2.574**	**-2.555**	-0.876	0.441	-1.001	-0.553	**-2.859**	1.659	0.598	0.122
	(0.962)	(0.294)	**(0.008)**	**(0.008)**	(0.194)	(0.669)	(0.162)	(0.292)	**(0.004)**	(0.946)	(0.723)	(0.548)
Ave. Non-linear	1.383	-0.584	**-2.658**	**-2.642**	-0.826	0.186	-1.021	-0.649	**-2.994**	1.412	0.367	-0.202
	(0.912)	(0.282)	**(0.006)**	**(0.006)**	(0.208)	(0.573)	(0.158)	(0.261)	**(0.003)**	(0.916)	(0.642)	(0.420)
Ave. AR+	-1.010	**-2.485**	**-2.494**	**-2.486**	**-2.074**	**-1.698**	-1.501	**-2.567**	**-2.693**	-1.166	-1.426	-1.554
	(0.160)	**(0.009)**	**(0.009)**	**(0.009)**	**(0.023)**	**(0.050)**	(0.072)	**(0.008)**	**(0.006)**	(0.126)	(0.082)	(0.065)
Tot. Ave.	-0.482	**-1.884**	**-2.407**	**-2.410**	**-1.989**	-1.643	-1.249	**-2.577**	**-2.643**	-0.716	-1.216	-1.313
	(0.317)	**(0.034)**	**(0.011)**	**(0.011)**	**(0.028)**	(0.055)	(0.111)	**(0.007)**	**(0.006)**	(0.240)	(0.117)	(0.099)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.18: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 0$. $N = 31$. Computed one month after end of reference quarter T.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	0.955	1.719	1.430	1.937	0.805	0.470	0.801	0.162	0.773	0.762	1.588	1.257
	(0.826)	(0.952)	(0.919)	(0.969)	(0.787)	(0.679)	(0.785)	(0.564)	(0.777)	(0.774)	(0.939)	(0.891)
RW	1.614	2.439	1.916	2.522	1.302	0.975	2.157	0.880	1.145	1.233	2.231	2.374
	(0.942)	(0.990)	(0.968)	(0.991)	(0.899)	(0.831)	(0.981)	(0.807)	(0.870)	(0.887)	(0.983)	(0.988)
DDD	1.626	2.490	1.953	2.586	1.313	0.994	2.240	0.901	1.166	1.243	2.272	2.421
	(0.943)	(0.991)	(0.970)	(0.993)	(0.901)	(0.836)	(0.984)	(0.813)	(0.874)	(0.888)	(0.985)	(0.989)
VAR(4)	0.696	1.782	1.393	2.031	0.735	0.359	0.638	0.006	0.306	0.384	1.629	1.301
	(0.754)	(0.958)	(0.913)	(0.975)	(0.766)	(0.639)	(0.736)	(0.502)	(0.619)	(0.648)	(0.943)	(0.899)
GETS	1.497	2.611	2.362	2.731	1.588	1.454	1.547	1.829	1.159	1.229	2.508	2.477
	(0.928)	(0.993)	(0.988)	(0.995)	(0.939)	(0.922)	(0.934)	(0.961)	(0.872)	(0.886)	(0.991)	(0.991)
GETS-IIS	1.477	2.602	2.549	2.840	1.619	1.537	1.540	1.574	1.224	1.268	2.535	2.190
	(0.925)	(0.993)	(0.992)	(0.996)	(0.942)	(0.933)	(0.933)	(0.937)	(0.885)	(0.893)	(0.992)	(0.982)
GETS-SIS	1.556	2.217	1.840	2.152	1.554	1.210	1.266	1.369	1.094	1.205	2.156	2.539
	(0.935)	(0.983)	(0.962)	(0.980)	(0.935)	(0.882)	(0.893)	(0.910)	(0.859)	(0.881)	(0.981)	(0.992)
GETS-DDD	2.001	2.650	2.419	2.602	2.025	1.720	1.847	2.272	1.640	1.710	2.582	2.840
	(0.973)	(0.994)	(0.989)	(0.993)	(0.974)	(0.952)	(0.963)	(0.985)	(0.944)	(0.951)	(0.993)	(0.996)
GETS-IIS-DDD	1.558	2.938	2.787	3.168	1.779	1.665	1.659	1.936	1.275	1.291	2.855	2.585
	(0.935)	(0.997)	(0.995)	(0.998)	(0.957)	(0.947)	(0.946)	(0.969)	(0.894)	(0.897)	(0.996)	(0.993)
GETS-SIS-DDD	1.774	2.387	2.046	2.330	1.787	1.464	1.599	1.799	1.374	1.460	2.324	2.718
	(0.957)	(0.988)	(0.975)	(0.987)	(0.958)	(0.923)	(0.940)	(0.959)	(0.910)	(0.923)	(0.987)	(0.995)
Ridge, CV	-1.632	1.281	0.436	1.383	-0.275	-0.833	-1.109	-1.529	**-1.881**	-1.423	1.101	0.612
	(0.056)	(0.895)	(0.667)	(0.912)	(0.393)	(0.206)	(0.138)	(0.068)	**(0.035)**	(0.082)	(0.860)	(0.728)
Lasso, CV	**-1.744**	1.188	0.404	1.302	-0.283	-0.802	-1.119	-1.466	**-1.962**	-1.434	1.034	0.561
	(0.045)	(0.878)	(0.655)	(0.899)	(0.390)	(0.214)	(0.136)	(0.076)	**(0.029)**	(0.081)	(0.845)	(0.710)
ELNET, CV	-1.681	1.162	0.301	1.245	-0.420	-0.973	-1.164	-1.679	**-1.830**	-1.383	1.010	0.482
	(0.051)	(0.873)	(0.617)	(0.889)	(0.339)	(0.169)	(0.127)	(0.052)	**(0.038)**	(0.088)	(0.840)	(0.683)
Ridge, AIC	0.886	2.427	2.384	2.493	1.346	0.829	0.627	0.584	0.549	0.584	2.485	1.884
	(0.809)	(0.989)	(0.988)	(0.991)	(0.906)	(0.793)	(0.732)	(0.718)	(0.706)	(0.718)	(0.991)	(0.966)
Lasso, AIC	2.536	2.544	2.480	2.615	2.250	2.123	2.502	2.085	2.574	2.658	2.494	2.407
	(0.992)	(0.992)	(0.991)	(0.993)	(0.984)	(0.979)	(0.991)	(0.977)	(0.992)	(0.994)	(0.991)	(0.989)
ELNET, AIC	2.537	2.532	2.475	2.596	2.266	2.147	2.498	2.120	2.555	2.642	2.486	2.410
	(0.992)	(0.992)	(0.991)	(0.993)	(0.985)	(0.980)	(0.991)	(0.979)	(0.992)	(0.994)	(0.991)	(0.989)
k-NN	1.476	2.224	1.672	2.207	1.132	0.556	0.670	0.198	0.876	0.826	2.074	1.989
	(0.925)	(0.983)	(0.948)	(0.983)	(0.867)	(0.709)	(0.746)	(0.578)	(0.806)	(0.792)	(0.977)	(0.972)
wk-NN	0.602	1.929	1.219	1.927	0.553	0.034	-0.012	-0.542	-0.441	-0.186	1.698	1.643
	(0.724)	(0.969)	(0.884)	(0.968)	(0.708)	(0.513)	(0.495)	(0.296)	(0.331)	(0.427)	(0.950)	(0.945)
RF	1.096	1.590	1.383	1.739	0.903	0.616	0.937	0.378	1.001	1.021	1.501	1.249
	(0.859)	(0.939)	(0.912)	(0.954)	(0.813)	(0.729)	(0.822)	(0.646)	(0.838)	(0.842)	(0.928)	(0.889)
FFNN	1.177	2.534	1.825	2.438	1.676	0.719	0.574	0.265	0.553	0.649	2.567	2.577
	(0.876)	(0.992)	(0.961)	(0.990)	(0.948)	(0.761)	(0.715)	(0.604)	(0.708)	(0.739)	(0.992)	(0.993)
RNN	2.800	2.767	2.687	2.839	2.436	2.283	2.931	2.297	2.859	2.994	2.693	2.643
	(0.996)	(0.995)	(0.994)	(0.996)	(0.990)	(0.985)	(0.997)	(0.986)	(0.996)	(0.997)	(0.994)	(0.994)
SVR-LIN	-1.123	1.370	0.626	1.600	-0.065	-0.611	-1.021	-1.266	-1.659	-1.412	1.166	0.716
	(0.135)	(0.910)	(0.732)	(0.940)	(0.474)	(0.273)	(0.157)	(0.107)	(0.054)	(0.084)	(0.874)	(0.760)
SVR-POLY	0.415	1.568	1.014	1.587	0.470	-0.030	-0.101	-0.508	-0.598	-0.367	1.426	1.216
	(0.659)	(0.936)	(0.841)	(0.939)	(0.679)	(0.488)	(0.460)	(0.307)	(0.277)	(0.358)	(0.918)	(0.883)
SVR-RBF	0.913	1.730	1.251	1.817	0.619	0.153	0.212	-0.273	-0.122	0.202	1.554	1.313
	(0.816)	(0.953)	(0.890)	(0.961)	(0.730)	(0.560)	(0.583)	(0.393)	(0.452)	(0.580)	(0.935)	(0.901)
SVR-ANOVA	-	1.644	0.986	1.694	0.360	-0.141	-0.287	-0.731	-0.959	-0.703	1.452	1.268
	-	(0.945)	(0.834)	(0.950)	(0.639)	(0.444)	(0.388)	(0.235)	(0.173)	(0.244)	(0.922)	(0.893)
AR+SVR-POLY	-1.644	-	-1.243	0.820	-1.307	**-2.155**	-1.608	**-2.912**	**-1.811**	-1.517	0.080	-0.663
	(0.055)	-	(0.112)	(0.791)	(0.100)	**(0.020)**	(0.059)	**(0.003)**	**(0.040)**	(0.070)	(0.532)	(0.256)
AR+SVR-RBF	-0.986	1.243	-	1.901	-0.658	-1.317	-1.091	**-2.044**	-1.309	-1.065	1.085	0.060
	(0.166)	(0.888)	-	(0.967)	(0.258)	(0.099)	(0.142)	**(0.025)**	(0.100)	(0.148)	(0.857)	(0.524)
AR+SVR-ANOVA	-1.694	-0.820	**-1.901**	-	-1.338	**-2.279**	**-1.825**	**-2.854**	**-1.941**	-1.628	-0.488	-0.768
	(0.050)	(0.209)	**(0.033)**	-	(0.095)	**(0.015)**	**(0.039)**	**(0.004)**	**(0.031)**	(0.057)	(0.315)	(0.224)
AR+FFNN	-0.360	1.307	0.658	1.338	-	-0.591	-0.431	-1.055	-0.633	-0.515	1.572	0.814
	(0.361)	(0.900)	(0.742)	(0.905)	-	(0.279)	(0.335)	(0.150)	(0.266)	(0.305)	(0.937)	(0.789)
AR+RNN	0.141	2.155	1.317	2.279	0.591	-	-0.036	-0.524	-0.180	-0.097	2.476	1.458
	(0.556)	(0.980)	(0.901)	(0.985)	(0.721)	-	(0.486)	(0.302)	(0.429)	(0.462)	(0.991)	(0.923)
Ave. BM	0.287	1.608	1.091	1.825	0.431	0.036	-	-0.457	-0.272	-0.126	1.403	1.183
	(0.612)	(0.941)	(0.858)	(0.961)	(0.665)	(0.514)	-	(0.325)	(0.394)	(0.450)	(0.915)	(0.877)
Ave. Linear	0.731	2.912	2.044	2.854	1.055	0.524	0.457	-	0.241	0.320	2.696	3.401
	(0.765)	(0.997)	(0.975)	(0.996)	(0.850)	(0.698)	(0.675)	-	(0.594)	(0.624)	(0.994)	(0.999)
Ave. Local	0.959	1.811	1.309	1.941	0.633	0.180	0.272	-0.241	-	0.271	1.618	1.331
	(0.827)	(0.960)	(0.900)	(0.969)	(0.734)	(0.571)	(0.606)	(0.406)	-	(0.606)	(0.942)	(0.904)
Ave. Non-linear	0.703	1.517	1.065	1.628	0.515	0.097	0.126	-0.320	-0.271	-	1.369	1.176
	(0.756)	(0.930)	(0.852)	(0.943)	(0.695)	(0.538)	(0.550)	(0.376)	(0.394)	-	(0.910)	(0.876)
Ave. AR+	-1.452	-0.080	-1.085	0.488	-1.572	**-2.476**	-1.403	**-2.696**	-1.618	-1.369	-	-0.658
	(0.078)	(0.468)	(0.143)	(0.685)	(0.063)	**(0.009)**	(0.085)	**(0.006)**	(0.058)	(0.090)	-	(0.258)
Tot. Ave.	-1.268	0.663	-0.060	0.768	-0.814	-1.458	-1.183	**-3.401**	-1.331	-1.176	0.658	-
	(0.107)	(0.744)	(0.476)	(0.776)	(0.211)	(0.077)	(0.123)	**(0.001)**	(0.096)	(0.124)	(0.742)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.19: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 1$. $N = 31$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	0.013	-0.014	1.278	-1.023	-1.023	-1.255	-0.821	-0.880	-0.865	0.921	0.485
	-	(0.505)	(0.494)	(0.894)	(0.157)	(0.157)	(0.110)	(0.209)	(0.193)	(0.197)	(0.818)	(0.684)
RW	-0.013	-	-0.323	0.563	-1.057	-1.051	-1.273	-0.877	-0.912	-0.891	0.912	0.408
	(0.495)	-	(0.374)	(0.711)	(0.150)	(0.151)	(0.106)	(0.194)	(0.185)	(0.190)	(0.816)	(0.657)
DDD	0.014	0.323	-	0.596	-1.047	-1.042	-1.266	-0.868	-0.903	-0.883	0.960	0.442
	(0.506)	(0.626)	-	(0.722)	(0.152)	(0.153)	(0.108)	(0.196)	(0.187)	(0.192)	(0.828)	(0.669)
VAR(4)	-1.278	-0.563	-0.596	-	-1.261	-1.242	-1.433	-1.114	-1.107	-1.129	0.260	-0.156
	(0.106)	(0.289)	(0.278)	-	(0.109)	(0.112)	(0.081)	(0.137)	(0.139)	(0.134)	(0.602)	(0.438)
GETS	1.023	1.057	1.047	1.261	-	-0.775	-1.522	0.874	0.224	0.788	1.665	1.683
	(0.843)	(0.850)	(0.848)	(0.891)	-	(0.222)	(0.069)	(0.805)	(0.588)	(0.782)	(0.947)	(0.949)
GETS-IIS	1.023	1.051	1.042	1.242	0.775	-	-1.636	0.900	0.513	0.889	1.600	1.612
	(0.843)	(0.849)	(0.847)	(0.888)	(0.778)	-	(0.056)	(0.812)	(0.694)	(0.810)	(0.940)	(0.941)
GETS-SIS	1.255	1.273	1.266	1.433	1.522	1.636	-	1.381	1.614	1.589	1.743	1.761
	(0.890)	(0.894)	(0.892)	(0.919)	(0.931)	(0.944)	-	(0.911)	(0.942)	(0.939)	(0.954)	(0.956)
GETS-DDD	0.821	0.877	0.868	1.114	-0.874	-0.900	-1.381	-	-0.744	-0.554	1.588	1.527
	(0.791)	(0.806)	(0.804)	(0.863)	(0.195)	(0.188)	(0.089)	-	(0.231)	(0.292)	(0.939)	(0.931)
GETS-IIS-DDD	0.880	0.912	0.903	1.107	-0.224	-0.513	-1.614	0.744	-	0.672	1.430	1.414
	(0.807)	(0.815)	(0.813)	(0.861)	(0.412)	(0.306)	(0.058)	(0.769)	-	(0.747)	(0.918)	(0.916)
GETS-SIS-DDD	0.865	0.891	0.883	1.129	-0.788	-0.889	-1.589	0.554	-0.672	-	1.526	1.499
	(0.803)	(0.810)	(0.808)	(0.866)	(0.218)	(0.190)	(0.061)	(0.708)	(0.253)	-	(0.931)	(0.928)
Ridge, CV	-0.921	-0.912	-0.960	-0.260	-1.665	-1.600	**-1.743**	-1.588	-1.430	-1.526	-	-0.998
	(0.182)	(0.184)	(0.172)	(0.398)	(0.053)	(0.060)	**(0.046)**	(0.061)	(0.082)	(0.069)	-	(0.163)
Lasso, CV	-0.485	-0.408	-0.442	0.156	-1.683	-1.612	**-1.761**	-1.527	-1.414	-1.499	0.998	-
	(0.316)	(0.343)	(0.331)	(0.562)	(0.051)	(0.059)	**(0.044)**	(0.069)	(0.084)	(0.072)	(0.837)	-
ELNET, CV	-0.922	-0.872	-0.922	-0.223	-1.637	-1.572	**-1.713**	-1.558	-1.395	-1.490	0.168	-0.885
	(0.182)	(0.195)	(0.182)	(0.413)	(0.056)	(0.063)	**(0.049)**	(0.065)	(0.087)	(0.073)	(0.566)	(0.192)
Ridge, AIC	0.913	0.995	0.980	1.232	-0.279	-0.410	-0.952	0.386	-0.166	0.173	1.562	1.535
	(0.816)	(0.836)	(0.832)	(0.886)	(0.391)	(0.342)	(0.174)	(0.649)	(0.435)	(0.568)	(0.936)	(0.932)
Lasso, AIC	1.244	1.224	1.217	1.415	0.836	0.777	0.421	1.072	0.946	1.003	1.467	1.466
	(0.888)	(0.885)	(0.883)	(0.916)	(0.795)	(0.778)	(0.661)	(0.854)	(0.824)	(0.838)	(0.924)	(0.923)
ELNET, AIC	1.893	1.804	1.797	2.044	1.604	1.571	1.299	1.752	1.746	1.757	2.045	2.071
	(0.966)	(0.959)	(0.959)	(0.975)	(0.940)	(0.937)	(0.898)	(0.955)	(0.954)	(0.955)	(0.975)	(0.976)
k-NN	-1.398	-1.530	-1.608	-0.821	-1.585	-1.529	-1.664	-1.560	-1.389	-1.481	-0.717	-0.964
	(0.086)	(0.068)	(0.059)	(0.209)	(0.062)	(0.068)	(0.053)	(0.065)	(0.088)	(0.075)	(0.239)	(0.171)
wk-NN	-0.783	-1.556	-1.543	-0.177	-1.398	-1.359	-1.528	-1.294	-1.207	-1.255	0.105	-0.328
	(0.220)	(0.065)	(0.067)	(0.430)	(0.086)	(0.092)	(0.069)	(0.103)	(0.118)	(0.110)	(0.542)	(0.372)
RF	-1.484	**-1.921**	**-1.998**	-0.958	-1.674	-1.611	**-1.728**	**-1.707**	-1.486	-1.580	-1.209	-1.215
	(0.074)	**(0.032)**	**(0.027)**	(0.173)	(0.052)	(0.059)	**(0.047)**	**(0.049)**	(0.074)	(0.062)	(0.118)	(0.117)
FFNN	0.578	0.651	0.628	1.043	-1.090	-1.094	-1.374	-0.693	-0.894	-0.792	2.163	1.893
	(0.716)	(0.740)	(0.733)	(0.847)	(0.142)	(0.141)	(0.090)	(0.247)	(0.189)	(0.217)	(0.981)	(0.966)
RNN	1.698	1.806	1.775	2.304	-0.130	-0.212	-0.602	0.328	-0.046	0.159	3.392	2.719
	(0.950)	(0.959)	(0.957)	(0.986)	(0.449)	(0.417)	(0.276)	(0.627)	(0.482)	(0.563)	(0.999)	(0.995)
SVR-LIN	-0.785	-1.207	-1.236	-0.434	-1.580	-1.524	-1.658	-1.656	-1.433	-1.503	-0.387	-0.616
	(0.219)	(0.118)	(0.113)	(0.334)	(0.062)	(0.069)	(0.054)	(0.054)	(0.081)	(0.072)	(0.351)	(0.271)
SVR-POLY	0.142	0.155	0.130	0.590	-1.049	-1.037	-1.278	-0.916	-0.895	-0.904	1.031	0.561
	(0.556)	(0.561)	(0.551)	(0.720)	(0.151)	(0.154)	(0.106)	(0.183)	(0.189)	(0.186)	(0.845)	(0.710)
SVR-RBF	-1.353	-0.842	-0.884	-0.217	-1.342	-1.312	-1.491	-1.245	-1.177	-1.216	0.152	-0.345
	(0.093)	(0.203)	(0.192)	(0.415)	(0.095)	(0.100)	(0.073)	(0.111)	(0.124)	(0.117)	(0.560)	(0.366)
SVR-ANOVA	-0.360	-0.468	-0.492	0.117	-1.186	-1.170	-1.366	-1.106	-1.065	-1.062	0.372	-0.001
	(0.361)	(0.322)	(0.313)	(0.546)	(0.123)	(0.126)	(0.091)	(0.139)	(0.148)	(0.148)	(0.644)	(0.500)
AR+SVR-POLY	-1.282	**-1.801**	**-1.841**	-1.036	**-2.179**	**-2.056**	**-2.092**	**-2.477**	**-1.963**	**-2.167**	-1.333	-1.512
	(0.105)	**(0.041)**	**(0.038)**	(0.154)	**(0.019)**	**(0.024)**	**(0.023)**	**(0.010)**	**(0.029)**	**(0.019)**	(0.096)	(0.071)
AR+SVR-RBF	-1.450	**-1.754**	**-1.814**	-1.197	**-1.982**	**-1.878**	**-1.933**	**-2.164**	**-1.762**	**-1.940**	-1.244	-1.502
	(0.079)	**(0.045)**	**(0.040)**	(0.120)	**(0.028)**	**(0.035)**	**(0.031)**	**(0.019)**	**(0.044)**	**(0.031)**	(0.112)	(0.072)
AR+SVR-ANOVA	**-1.763**	**-2.351**	**-2.424**	-1.610	**-2.392**	**-2.246**	**-2.239**	**-2.677**	**-2.120**	**-2.391**	**-2.158**	**-2.263**
	(0.044)	**(0.013)**	**(0.011)**	(0.059)	**(0.012)**	**(0.016)**	**(0.016)**	**(0.006)**	**(0.021)**	**(0.012)**	**(0.020)**	**(0.016)**
AR+FFNN	-0.729	-0.945	-0.979	-0.388	**-1.999**	**-1.889**	**-1.980**	**-2.175**	**-1.770**	**-1.953**	-0.402	-0.757
	(0.236)	(0.176)	(0.168)	(0.350)	**(0.027)**	**(0.034)**	**(0.028)**	**(0.019)**	**(0.043)**	**(0.030)**	(0.345)	(0.228)
AR+RNN	2.594	3.393	3.387	3.174	0.884	0.754	0.287	1.444	0.911	1.191	3.873	3.309
	(0.993)	(0.999)	(0.999)	(0.998)	(0.808)	(0.772)	(0.612)	(0.920)	(0.815)	(0.879)	(1.000)	(0.999)
Ave. BM	-0.848	-1.557	-1.693	-0.154	-1.365	-1.331	-1.502	-1.256	-1.186	-1.217	0.135	-0.323
	(0.202)	(0.065)	(0.050)	(0.439)	(0.091)	(0.097)	(0.072)	(0.109)	(0.122)	(0.117)	(0.553)	(0.375)
Ave. Linear	0.281	0.307	0.294	0.570	**-2.575**	**-2.328**	**-2.341**	**-1.769**	**-2.349**	**-2.258**	0.873	0.753
	(0.610)	(0.620)	(0.615)	(0.714)	**(0.008)**	**(0.013)**	**(0.013)**	**(0.044)**	**(0.013)**	**(0.016)**	(0.805)	(0.771)
Ave. Local	-1.476	**-1.962**	**-2.046**	-0.928	-1.637	-1.576	**-1.702**	-1.632	-1.438	-1.532	-1.032	-1.127
	(0.075)	**(0.030)**	**(0.025)**	(0.180)	(0.056)	(0.063)	**(0.050)**	(0.057)	(0.080)	(0.068)	(0.155)	(0.134)
Ave. Non-linear	-0.579	-0.804	-0.836	-0.104	-1.420	-1.379	-1.542	-1.397	-1.266	-1.311	0.162	-0.283
	(0.284)	(0.214)	(0.205)	(0.459)	(0.083)	(0.089)	(0.067)	(0.086)	(0.108)	(0.100)	(0.564)	(0.390)
Ave. AR+	-1.276	**-1.729**	**-1.772**	-1.016	**-2.082**	**-1.970**	**-2.023**	**-2.304**	**-1.865**	**-2.052**	-1.354	-1.514
	(0.106)	**(0.047)**	**(0.043)**	(0.159)	**(0.023)**	**(0.029)**	**(0.026)**	**(0.014)**	**(0.036)**	**(0.025)**	(0.093)	(0.070)
Tot. Ave.	-0.882	-1.110	-1.147	-0.539	**-2.283**	**-2.126**	**-2.163**	**-2.598**	**-1.999**	**-2.277**	-0.709	-1.129
	(0.192)	(0.138)	(0.130)	(0.297)	**(0.015)**	**(0.021)**	**(0.019)**	**(0.007)**	**(0.027)**	**(0.015)**	(0.242)	(0.134)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.20: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 1$. $N = 31$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	0.922	-0.913	-1.244	**-1.893**	1.398	0.783	1.484	-0.578	**-1.698**	0.785	-0.142	1.353
	(0.818)	(0.184)	(0.112)	**(0.034)**	(0.914)	(0.780)	(0.926)	(0.284)	**(0.050)**	(0.781)	(0.444)	(0.907)
RW	0.872	-0.995	-1.224	**-1.804**	1.530	1.556	1.921	-0.651	**-1.806**	1.207	-0.155	0.842
	(0.805)	(0.164)	(0.115)	**(0.041)**	(0.932)	(0.935)	(0.968)	(0.260)	**(0.041)**	(0.882)	(0.439)	(0.797)
DDD	0.922	-0.980	-1.217	**-1.797**	1.608	1.543	1.998	-0.628	**-1.775**	1.236	-0.130	0.884
	(0.818)	(0.168)	(0.117)	**(0.041)**	(0.941)	(0.933)	(0.973)	(0.267)	**(0.043)**	(0.887)	(0.449)	(0.808)
VAR(4)	0.223	-1.232	-1.415	**-2.044**	0.821	0.177	0.958	-1.043	**-2.304**	0.434	-0.590	0.217
	(0.587)	(0.114)	(0.084)	**(0.025)**	(0.791)	(0.570)	(0.827)	(0.153)	**(0.014)**	(0.666)	(0.280)	(0.585)
GETS	1.637	0.279	-0.836	-1.604	1.585	1.398	1.674	1.090	0.130	1.580	1.049	1.342
	(0.944)	(0.609)	(0.205)	(0.060)	(0.938)	(0.914)	(0.948)	(0.858)	(0.551)	(0.938)	(0.849)	(0.905)
GETS-IIS	1.572	0.410	-0.777	-1.571	1.529	1.359	1.611	1.094	0.212	1.524	1.037	1.312
	(0.937)	(0.658)	(0.222)	(0.063)	(0.932)	(0.908)	(0.941)	(0.859)	(0.583)	(0.931)	(0.846)	(0.900)
GETS-SIS	1.713	0.952	-0.421	-1.299	1.664	1.528	1.728	1.374	0.602	1.658	1.278	1.491
	(0.951)	(0.826)	(0.339)	(0.102)	(0.947)	(0.931)	(0.953)	(0.910)	(0.724)	(0.946)	(0.894)	(0.927)
GETS-DDD	1.558	-0.386	-1.072	**-1.752**	1.560	1.294	1.707	0.693	-0.328	1.656	0.916	1.245
	(0.935)	(0.351)	(0.146)	**(0.045)**	(0.935)	(0.897)	(0.951)	(0.753)	(0.373)	(0.946)	(0.817)	(0.889)
GETS-IIS-DDD	1.395	0.166	-0.946	**-1.746**	1.389	1.207	1.486	0.894	0.046	1.433	0.895	1.177
	(0.913)	(0.565)	(0.176)	**(0.046)**	(0.912)	(0.882)	(0.926)	(0.811)	(0.518)	(0.919)	(0.811)	(0.876)
GETS-SIS-DDD	1.490	-0.173	-1.003	**-1.757**	1.481	1.255	1.580	0.792	-0.159	1.503	0.904	1.216
	(0.927)	(0.432)	(0.162)	**(0.045)**	(0.925)	(0.890)	(0.938)	(0.783)	(0.437)	(0.928)	(0.814)	(0.883)
Ridge, CV	-0.168	-1.562	-1.467	**-2.045**	0.717	-0.105	1.209	**-2.163**	**-3.392**	0.387	-1.031	-0.152
	(0.434)	(0.064)	(0.076)	**(0.025)**	(0.761)	(0.458)	(0.882)	**(0.019)**	**(0.001)**	(0.649)	(0.155)	(0.440)
Lasso, CV	0.885	-1.535	-1.466	**-2.071**	0.964	0.328	1.215	**-1.893**	**-2.719**	0.616	-0.561	0.345
	(0.808)	(0.068)	(0.077)	**(0.024)**	(0.829)	(0.628)	(0.883)	**(0.034)**	**(0.005)**	(0.729)	(0.290)	(0.634)
ELNET, CV	-	-1.507	-1.452	**-2.024**	0.775	-0.066	1.296	**-1.961**	**-3.281**	0.405	-1.101	-0.113
	-	(0.071)	(0.078)	**(0.026)**	(0.778)	(0.474)	(0.898)	**(0.030)**	**(0.001)**	(0.656)	(0.140)	(0.456)
Ridge, AIC	1.507	-	-1.189	**-1.965**	1.534	1.345	1.657	0.952	-0.048	1.675	0.872	1.275
	(0.929)	-	(0.122)	**(0.029)**	(0.932)	(0.906)	(0.946)	(0.826)	(0.481)	(0.948)	(0.805)	(0.894)
Lasso, AIC	1.452	1.189	-	**-1.708**	1.492	1.396	1.544	1.177	0.747	1.532	1.177	1.397
	(0.922)	(0.878)	-	**(0.049)**	(0.927)	(0.914)	(0.933)	(0.876)	(0.770)	(0.932)	(0.876)	(0.914)
ELNET, AIC	2.024	1.965	1.708	-	2.033	1.952	2.063	1.820	1.432	2.037	1.759	1.986
	(0.974)	(0.971)	(0.951)	-	(0.975)	(0.970)	(0.976)	(0.961)	(0.919)	(0.975)	(0.956)	(0.972)
k-NN	-0.775	-1.534	-1.492	**-2.033**	-	-0.949	0.791	**-1.830**	**-3.409**	0.023	-1.354	-0.824
	(0.222)	(0.068)	(0.073)	**(0.025)**	-	(0.175)	(0.782)	**(0.039)**	**(0.001)**	(0.509)	(0.093)	(0.208)
wk-NN	0.066	-1.345	-1.396	**-1.952**	0.949	-	1.221	-1.351	**-2.725**	0.461	-0.870	-0.026
	(0.526)	(0.094)	(0.086)	**(0.030)**	(0.825)	-	(0.884)	(0.093)	**(0.005)**	(0.676)	(0.196)	(0.490)
RF	-1.296	-1.657	-1.544	**-2.063**	-0.791	-1.221	-	**-2.041**	**-3.609**	-0.415	**-1.874**	-1.397
	(0.102)	(0.054)	(0.067)	**(0.024)**	(0.218)	(0.116)	-	**(0.025)**	**(0.001)**	(0.341)	**(0.035)**	(0.086)
FFNN	1.961	-0.952	-1.177	**-1.820**	1.830	1.351	2.041	-	-1.644	1.690	0.499	1.255
	(0.970)	(0.174)	(0.124)	**(0.039)**	(0.961)	(0.907)	(0.975)	-	(0.055)	(0.949)	(0.689)	(0.890)
RNN	3.281	0.048	-0.747	-1.432	3.409	2.725	3.609	1.644	-	3.106	1.663	2.597
	(0.999)	(0.519)	(0.230)	(0.081)	(0.999)	(0.995)	(0.999)	(0.945)	-	(0.998)	(0.947)	(0.993)
SVR-LIN	-0.405	-1.675	-1.532	**-2.037**	-0.023	-0.461	0.415	-1.690	**-3.106**	-	-1.249	-0.428
	(0.344)	(0.052)	(0.068)	**(0.025)**	(0.491)	(0.324)	(0.659)	(0.051)	**(0.002)**	-	(0.111)	(0.336)
SVR-POLY	1.101	-0.872	-1.177	**-1.759**	1.354	0.870	1.874	-0.499	-1.663	1.249	-	1.039
	(0.860)	(0.195)	(0.124)	**(0.044)**	(0.907)	(0.804)	(0.965)	(0.311)	(0.053)	(0.889)	-	(0.846)
SVR-RBF	0.113	-1.275	-1.397	**-1.986**	0.824	0.026	1.397	-1.255	**-2.597**	0.428	-1.039	-
	(0.544)	(0.106)	(0.086)	**(0.028)**	(0.792)	(0.510)	(0.914)	(0.110)	**(0.007)**	(0.664)	(0.154)	-
SVR-ANOVA	0.348	-1.174	-1.318	**-1.892**	0.757	0.301	1.533	-0.965	**-2.459**	1.150	-0.693	0.332
	(0.635)	(0.125)	(0.099)	**(0.034)**	(0.772)	(0.617)	(0.932)	(0.171)	**(0.010)**	(0.870)	(0.247)	(0.629)
AR+SVR-POLY	-1.298	**-2.390**	**-1.785**	**-2.266**	-0.927	-1.275	-0.632	**-2.885**	**-4.012**	-1.488	**-1.728**	-1.054
	(0.102)	**(0.012)**	**(0.042)**	**(0.015)**	(0.181)	(0.106)	(0.266)	**(0.004)**	**(0.000)**	(0.074)	**(0.047)**	(0.150)
AR+SVR-RBF	-1.258	**-2.142**	**-1.788**	**-2.260**	-0.980	-1.317	-0.511	**-2.341**	**-3.404**	-0.857	-1.680	-1.118
	(0.109)	**(0.020)**	**(0.042)**	**(0.016)**	(0.168)	(0.099)	(0.307)	**(0.013)**	**(0.001)**	(0.199)	(0.052)	(0.136)
AR+SVR-ANOVA	**-2.076**	**-2.527**	**-1.871**	**-2.328**	**-1.852**	**-2.046**	-1.324	**-3.316**	**-4.186**	**-1.727**	**-2.060**	-1.576
	(0.023)	**(0.008)**	**(0.036)**	**(0.013)**	**(0.037)**	**(0.025)**	(0.098)	**(0.001)**	**(0.000)**	**(0.047)**	**(0.024)**	(0.063)
AR+FFNN	-0.407	**-2.015**	-1.583	**-2.104**	0.016	-0.380	0.339	**-2.619**	**-3.258**	0.045	-1.028	-0.333
	(0.344)	**(0.026)**	(0.062)	**(0.022)**	(0.506)	(0.353)	(0.631)	**(0.007)**	**(0.001)**	(0.518)	(0.156)	(0.371)
AR+RNN	3.790	1.140	-0.136	-0.814	4.180	3.772	4.549	2.561	1.823	4.484	2.735	3.473
	(1.000)	(0.868)	(0.447)	(0.211)	(1.000)	(1.000)	(1.000)	(0.992)	(0.961)	(1.000)	(0.995)	(0.999)
Ave. BM	0.097	-1.297	-1.387	**-1.935**	0.835	0.037	1.423	-1.257	**-2.412**	0.454	-0.894	-0.002
	(0.538)	(0.102)	(0.088)	**(0.031)**	(0.795)	(0.515)	(0.918)	(0.109)	**(0.011)**	(0.673)	(0.189)	(0.499)
Ave. Linear	0.834	**-1.946**	-1.451	**-2.107**	0.910	0.681	1.045	-0.206	-1.003	0.959	0.230	0.643
	(0.794)	**(0.031)**	(0.079)	**(0.022)**	(0.815)	(0.749)	(0.848)	(0.419)	(0.162)	(0.827)	(0.590)	(0.737)
Ave. Local	-1.107	-1.601	-1.518	**-2.048**	-0.867	-1.467	0.585	**-1.960**	**-3.527**	-0.166	-1.600	-1.153
	(0.139)	(0.060)	(0.070)	**(0.025)**	(0.196)	(0.076)	(0.719)	**(0.030)**	**(0.001)**	(0.435)	(0.060)	(0.129)
Ave. Non-linear	0.115	-1.430	-1.412	**-1.954**	0.721	0.042	1.744	-1.578	**-3.200**	1.096	-0.920	0.018
	(0.546)	(0.081)	(0.084)	**(0.030)**	(0.762)	(0.517)	(0.954)	(0.062)	**(0.002)**	(0.859)	(0.182)	(0.507)
Ave. AR+	-1.308	**-2.224**	**-1.729**	**-2.215**	-0.901	-1.239	-0.528	**-2.832**	**-3.935**	-1.125	-1.654	-1.024
	(0.100)	**(0.017)**	**(0.047)**	**(0.017)**	(0.187)	(0.113)	(0.301)	**(0.004)**	**(0.000)**	(0.135)	(0.054)	(0.157)
Tot. Ave.	-0.694	**-2.254**	-1.656	**-2.181**	-0.194	-0.565	0.122	**-3.195**	**-3.648**	-0.193	-1.230	-0.503
	(0.247)	**(0.016)**	(0.054)	**(0.019)**	(0.424)	(0.288)	(0.548)	**(0.002)**	**(0.000)**	(0.424)	(0.114)	(0.309)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.21: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 1$. $N = 31$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	0.360	1.282	1.450	1.763	0.729	**-2.594**	0.848	-0.281	1.476	0.579	1.276	0.882
	(0.639)	(0.895)	(0.921)	(0.956)	(0.764)	**(0.007)**	(0.798)	(0.390)	(0.925)	(0.716)	(0.894)	(0.808)
RW	0.468	1.801	1.754	2.351	0.945	**-3.393**	1.557	-0.307	1.962	0.804	1.729	1.110
	(0.678)	(0.959)	(0.955)	(0.987)	(0.824)	**(0.001)**	(0.935)	(0.380)	(0.970)	(0.786)	(0.953)	(0.862)
DDD	0.492	1.841	1.814	2.424	0.979	**-3.387**	1.693	-0.294	2.046	0.836	1.772	1.147
	(0.687)	(0.962)	(0.960)	(0.989)	(0.832)	**(0.001)**	(0.950)	(0.385)	(0.975)	(0.795)	(0.957)	(0.870)
VAR(4)	-0.117	1.036	1.197	1.610	0.388	**-3.174**	0.154	-0.570	0.928	0.104	1.016	0.539
	(0.454)	(0.846)	(0.880)	(0.941)	(0.650)	**(0.002)**	(0.561)	(0.286)	(0.820)	(0.541)	(0.841)	(0.703)
GETS	1.186	2.179	1.982	2.392	1.999	-0.884	1.365	2.575	1.637	1.420	2.082	2.283
	(0.877)	(0.981)	(0.972)	(0.988)	(0.973)	(0.192)	(0.909)	(0.992)	(0.944)	(0.917)	(0.977)	(0.985)
GETS-IIS	1.170	2.056	1.878	2.246	1.889	-0.754	1.331	2.328	1.576	1.379	1.970	2.126
	(0.874)	(0.976)	(0.965)	(0.984)	(0.966)	(0.228)	(0.903)	(0.987)	(0.937)	(0.911)	(0.971)	(0.979)
GETS-SIS	1.366	2.092	1.933	2.239	1.980	-0.287	1.502	2.341	1.702	1.542	2.023	2.163
	(0.909)	(0.977)	(0.969)	(0.984)	(0.972)	(0.388)	(0.928)	(0.987)	(0.950)	(0.933)	(0.974)	(0.981)
GETS-DDD	1.106	2.477	2.164	2.677	2.175	-1.444	1.256	1.769	1.632	1.397	2.304	2.598
	(0.861)	(0.990)	(0.981)	(0.994)	(0.981)	(0.080)	(0.891)	(0.956)	(0.943)	(0.914)	(0.986)	(0.993)
GETS-IIS-DDD	1.065	1.963	1.762	2.120	1.770	-0.911	1.186	2.349	1.438	1.266	1.865	1.999
	(0.852)	(0.971)	(0.956)	(0.979)	(0.957)	(0.185)	(0.878)	(0.987)	(0.920)	(0.892)	(0.964)	(0.973)
GETS-SIS-DDD	1.062	2.167	1.940	2.391	1.953	-1.191	1.217	2.258	1.532	1.311	2.052	2.277
	(0.852)	(0.981)	(0.969)	(0.988)	(0.970)	(0.121)	(0.883)	(0.984)	(0.932)	(0.900)	(0.975)	(0.985)
Ridge, CV	-0.372	1.333	1.244	2.158	0.402	**-3.873**	-0.135	-0.873	1.032	-0.162	1.354	0.709
	(0.356)	(0.904)	(0.888)	(0.980)	(0.655)	**(0.000)**	(0.447)	(0.195)	(0.845)	(0.436)	(0.907)	(0.758)
Lasso, CV	0.001	1.512	1.502	2.263	0.757	**-3.309**	0.323	-0.753	1.127	0.283	1.514	1.129
	(0.500)	(0.929)	(0.928)	(0.984)	(0.772)	**(0.001)**	(0.625)	(0.229)	(0.866)	(0.610)	(0.930)	(0.866)
ELNET, CV	-0.348	1.298	1.258	2.076	0.407	**-3.790**	-0.097	-0.834	1.107	-0.115	1.308	0.694
	(0.365)	(0.898)	(0.891)	(0.977)	(0.656)	**(0.000)**	(0.462)	(0.206)	(0.861)	(0.454)	(0.900)	(0.753)
Ridge, AIC	1.174	2.390	2.142	2.527	2.015	-1.140	1.297	1.946	1.601	1.430	2.224	2.254
	(0.875)	(0.988)	(0.980)	(0.992)	(0.974)	(0.132)	(0.898)	(0.969)	(0.940)	(0.919)	(0.983)	(0.984)
Lasso, AIC	1.318	1.785	1.788	1.871	1.583	0.136	1.387	1.451	1.518	1.412	1.729	1.656
	(0.901)	(0.958)	(0.958)	(0.964)	(0.938)	(0.553)	(0.912)	(0.921)	(0.930)	(0.916)	(0.953)	(0.946)
ELNET, AIC	1.892	2.266	2.260	2.328	2.104	0.814	1.935	2.107	2.048	1.954	2.215	2.181
	(0.966)	(0.985)	(0.984)	(0.987)	(0.978)	(0.789)	(0.969)	(0.978)	(0.975)	(0.970)	(0.983)	(0.981)
k-NN	-0.757	0.927	0.980	1.852	-0.016	**-4.180**	-0.835	-0.910	0.867	-0.721	0.901	0.194
	(0.228)	(0.819)	(0.832)	(0.963)	(0.494)	**(0.000)**	(0.205)	(0.185)	(0.804)	(0.238)	(0.813)	(0.576)
wk-NN	-0.301	1.275	1.317	2.046	0.380	**-3.772**	-0.037	-0.681	1.467	-0.042	1.239	0.565
	(0.383)	(0.894)	(0.901)	(0.975)	(0.647)	**(0.000)**	(0.485)	(0.251)	(0.924)	(0.483)	(0.887)	(0.712)
RF	-1.533	0.632	0.511	1.324	-0.339	**-4.549**	-1.423	-1.045	-0.585	**-1.744**	0.528	-0.122
	(0.068)	(0.734)	(0.693)	(0.902)	(0.369)	**(0.000)**	(0.082)	(0.152)	(0.281)	**(0.046)**	(0.699)	(0.452)
FFNN	0.965	2.885	2.341	3.316	2.619	**-2.561**	1.257	0.206	1.960	1.578	2.832	3.195
	(0.829)	(0.996)	(0.987)	(0.999)	(0.993)	**(0.008)**	(0.891)	(0.581)	(0.970)	(0.938)	(0.996)	(0.998)
RNN	2.459	4.012	3.404	4.186	3.258	**-1.823**	2.412	1.003	3.527	3.200	3.935	3.648
	(0.990)	(1.000)	(0.999)	(1.000)	(0.999)	**(0.039)**	(0.989)	(0.838)	(0.999)	(0.998)	(1.000)	(1.000)
SVR-LIN	-1.150	1.488	0.857	1.727	-0.045	**-4.484**	-0.454	-0.959	0.166	-1.096	1.125	0.193
	(0.130)	(0.926)	(0.801)	(0.953)	(0.482)	**(0.000)**	(0.327)	(0.173)	(0.565)	(0.141)	(0.865)	(0.576)
SVR-POLY	0.693	1.728	1.680	2.060	1.028	**-2.735**	0.894	-0.230	1.600	0.920	1.654	1.230
	(0.753)	(0.953)	(0.948)	(0.976)	(0.844)	**(0.005)**	(0.811)	(0.410)	(0.940)	(0.818)	(0.946)	(0.886)
SVR-RBF	-0.332	1.054	1.118	1.576	0.333	**-3.473**	0.002	-0.643	1.153	-0.018	1.024	0.503
	(0.371)	(0.850)	(0.864)	(0.937)	(0.629)	**(0.001)**	(0.501)	(0.263)	(0.871)	(0.493)	(0.843)	(0.691)
SVR-ANOVA	-	1.490	1.224	1.685	0.581	**-3.591**	0.294	-0.506	1.048	0.433	1.346	0.738
	-	(0.927)	(0.885)	(0.949)	(0.717)	**(0.001)**	(0.615)	(0.308)	(0.849)	(0.666)	(0.906)	(0.767)
AR+SVR-POLY	-1.490	-	-0.238	1.384	**-1.864**	**-4.777**	-1.136	-1.665	-0.786	**-2.048**	-0.540	-1.242
	(0.073)	-	(0.407)	(0.912)	**(0.036)**	**(0.000)**	(0.133)	(0.053)	(0.219)	**(0.025)**	(0.297)	(0.112)
AR+SVR-RBF	-1.224	0.238	-	1.691	-0.896	**-4.397**	-1.186	-1.411	-0.749	-1.507	-0.013	-0.611
	(0.115)	(0.593)	-	(0.949)	(0.189)	**(0.000)**	(0.122)	(0.084)	(0.230)	(0.071)	(0.495)	(0.273)
AR+SVR-ANOVA	-1.685	-1.384	-1.691	-	**-2.716**	**-4.971**	**-1.771**	**-1.921**	-1.613	**-2.473**	**-2.142**	**-2.074**
	(0.051)	(0.088)	(0.051)	-	**(0.005)**	**(0.000)**	**(0.043)**	**(0.032)**	(0.059)	**(0.010)**	**(0.020)**	**(0.023)**
AR+FFNN	-0.581	1.864	0.896	2.716	-	**-4.102**	-0.355	-1.311	0.179	-0.590	1.580	0.688
	(0.283)	(0.964)	(0.811)	(0.995)	-	**(0.000)**	(0.363)	(0.100)	(0.570)	(0.280)	(0.938)	(0.752)
AR+RNN	3.591	4.777	4.397	4.971	4.102	-	3.771	1.960	4.357	4.224	5.011	4.247
	(0.999)	(1.000)	(1.000)	(1.000)	(1.000)	-	(1.000)	(0.970)	(1.000)	(1.000)	(1.000)	(1.000)
Ave. BM	-0.294	1.136	1.186	1.771	0.355	**-3.771**	-	-0.655	1.360	-0.019	1.096	0.531
	(0.385)	(0.867)	(0.878)	(0.957)	(0.637)	**(0.000)**	-	(0.259)	(0.908)	(0.492)	(0.859)	(0.700)
Ave. Linear	0.506	1.665	1.411	1.921	1.311	**-1.960**	0.655	-	0.980	0.722	1.534	1.628
	(0.692)	(0.947)	(0.916)	(0.968)	(0.900)	**(0.030)**	(0.741)	-	(0.833)	(0.762)	(0.932)	(0.943)
Ave. Local	-1.048	0.786	0.749	1.613	-0.179	**-4.357**	-1.360	-0.980	-	-1.116	0.719	0.034
	(0.151)	(0.781)	(0.770)	(0.941)	(0.430)	**(0.000)**	(0.092)	(0.167)	-	(0.137)	(0.761)	(0.513)
Ave. Non-linear	-0.433	2.048	1.507	2.473	0.590	**-4.224**	0.019	-0.722	1.116	-	1.990	0.807
	(0.334)	(0.975)	(0.929)	(0.990)	(0.720)	**(0.000)**	(0.508)	(0.238)	(0.863)	-	(0.972)	(0.787)
Ave. AR+	-1.346	0.540	0.013	2.142	-1.580	**-5.011**	-1.096	-1.534	-0.719	**-1.990**	-	-0.996
	(0.094)	(0.703)	(0.505)	(0.980)	(0.062)	**(0.000)**	(0.141)	(0.068)	(0.239)	**(0.028)**	-	(0.164)
Tot. Ave.	-0.738	1.242	0.611	2.074	-0.688	**-4.247**	-0.531	-1.628	-0.034	-0.807	0.996	-
	(0.233)	(0.888)	(0.727)	(0.977)	(0.248)	**(0.000)**	(0.300)	(0.057)	(0.487)	(0.213)	(0.836)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.22: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 2$. $N = 30$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.318	-0.619	-0.718	-1.563	-1.550	-1.495	**-2.704**	**-2.667**	**-2.584**	0.800	1.008
	-	(0.376)	(0.270)	(0.239)	(0.064)	(0.066)	(0.073)	**(0.006)**	**(0.006)**	**(0.008)**	(0.785)	(0.839)
RW	0.318	-	**-1.972**	-0.482	-1.492	-1.482	-1.462	**-2.336**	**-2.271**	**-2.246**	1.287	1.371
	(0.624)	-	**(0.029)**	(0.317)	(0.073)	(0.075)	(0.077)	**(0.013)**	**(0.015)**	**(0.016)**	(0.896)	(0.910)
DDD	0.619	1.972	-	0.140	-1.402	-1.392	-1.385	**-2.091**	**-2.064**	**-2.027**	1.435	1.516
	(0.730)	(0.971)	-	(0.555)	(0.086)	(0.087)	(0.088)	**(0.023)**	**(0.024)**	**(0.026)**	(0.919)	(0.930)
VAR(4)	0.718	0.482	-0.140	-	-1.495	-1.478	-1.441	**-2.686**	**-2.598**	**-2.497**	1.373	1.851
	(0.761)	(0.683)	(0.445)	-	(0.073)	(0.075)	(0.080)	**(0.006)**	**(0.007)**	**(0.009)**	(0.910)	(0.963)
GETS	1.563	1.492	1.402	1.495	-	1.233	-0.890	0.822	0.733	0.782	1.786	1.740
	(0.936)	(0.927)	(0.914)	(0.927)	-	(0.886)	(0.190)	(0.791)	(0.765)	(0.780)	(0.958)	(0.954)
GETS-IIS	1.550	1.482	1.392	1.478	-1.233	-	-1.017	0.796	0.705	0.753	1.782	1.734
	(0.934)	(0.925)	(0.913)	(0.925)	(0.114)	-	(0.159)	(0.784)	(0.757)	(0.771)	(0.957)	(0.953)
GETS-SIS	1.495	1.462	1.385	1.441	0.890	1.017	-	0.892	0.816	0.869	1.741	1.686
	(0.927)	(0.923)	(0.912)	(0.920)	(0.810)	(0.841)	-	(0.810)	(0.790)	(0.804)	(0.954)	(0.949)
GETS-DDD	2.704	2.336	2.091	2.686	-0.822	-0.796	-0.892	-	-0.999	-0.823	2.987	3.019
	(0.994)	(0.987)	(0.977)	(0.994)	(0.209)	(0.216)	(0.190)	-	(0.163)	(0.209)	(0.997)	(0.997)
GETS-IIS-DDD	2.667	2.271	2.064	2.598	-0.733	-0.705	-0.816	0.999	-	0.044	2.762	2.823
	(0.994)	(0.985)	(0.976)	(0.993)	(0.235)	(0.243)	(0.210)	(0.837)	-	(0.517)	(0.995)	(0.996)
GETS-SIS-DDD	2.584	2.246	2.027	2.497	-0.782	-0.753	-0.869	0.823	-0.044	-	2.844	2.870
	(0.992)	(0.984)	(0.974)	(0.991)	(0.220)	(0.229)	(0.196)	(0.791)	(0.483)	-	(0.996)	(0.996)
Ridge, CV	-0.800	-1.287	-1.435	-1.373	**-1.786**	**-1.782**	**-1.741**	**-2.987**	**-2.762**	**-2.844**	-	-0.171
	(0.215)	(0.104)	(0.081)	(0.090)	**(0.042)**	**(0.043)**	**(0.046)**	**(0.003)**	**(0.005)**	**(0.004)**	-	(0.433)
Lasso, CV	-1.008	-1.371	-1.516	**-1.851**	**-1.740**	**-1.734**	-1.686	**-3.019**	**-2.823**	**-2.870**	0.171	-
	(0.161)	(0.090)	(0.070)	**(0.037)**	**(0.046)**	**(0.047)**	(0.051)	**(0.003)**	**(0.004)**	**(0.004)**	(0.567)	-
ELNET, CV	-0.959	-1.303	-1.454	**-1.798**	**-1.736**	**-1.729**	-1.682	**-3.003**	**-2.808**	**-2.856**	0.291	0.939
	(0.173)	(0.101)	(0.078)	**(0.041)**	**(0.047)**	**(0.047)**	(0.052)	**(0.003)**	**(0.004)**	**(0.004)**	(0.614)	(0.822)
Ridge, AIC	0.530	0.459	0.184	0.231	-1.672	-1.670	-1.652	**-2.422**	**-2.211**	**-2.377**	2.015	1.573
	(0.700)	(0.675)	(0.572)	(0.590)	(0.053)	(0.053)	(0.055)	**(0.011)**	**(0.018)**	**(0.012)**	(0.973)	(0.937)
Lasso, AIC	1.246	1.231	1.179	1.216	0.297	0.331	-0.037	0.689	0.650	0.654	1.380	1.355
	(0.889)	(0.886)	(0.876)	(0.883)	(0.616)	(0.629)	(0.485)	(0.752)	(0.740)	(0.741)	(0.911)	(0.907)
ELNET, AIC	1.198	1.192	1.154	1.171	0.691	0.713	0.490	0.813	0.785	0.791	1.311	1.288
	(0.880)	(0.879)	(0.871)	(0.874)	(0.752)	(0.759)	(0.686)	(0.789)	(0.780)	(0.782)	(0.900)	(0.896)
k-NN	2.943	1.953	1.694	2.928	-0.885	-0.865	-0.928	-0.850	-1.023	-0.929	2.380	2.692
	(0.997)	(0.970)	(0.949)	(0.997)	(0.192)	(0.197)	(0.181)	(0.201)	(0.157)	(0.180)	(0.988)	(0.994)
wk-NN	1.744	1.327	0.994	1.871	-1.194	-1.179	-1.193	**-1.716**	**-1.767**	-1.677	2.094	2.365
	(0.954)	(0.903)	(0.836)	(0.964)	(0.121)	(0.124)	(0.121)	**(0.048)**	**(0.044)**	(0.052)	(0.977)	(0.988)
RF	-1.362	-1.114	-1.306	**-4.908**	-1.667	-1.657	-1.603	**-2.855**	**-2.739**	**-2.726**	0.391	0.539
	(0.092)	(0.137)	(0.101)	**(0.000)**	(0.053)	(0.054)	(0.060)	**(0.004)**	**(0.005)**	**(0.005)**	(0.651)	(0.703)
FFNN	0.521	0.377	0.145	0.202	-1.392	-1.384	-1.412	**-1.797**	**-1.738**	**-1.760**	1.742	1.562
	(0.697)	(0.646)	(0.557)	(0.580)	(0.087)	(0.088)	(0.084)	**(0.041)**	**(0.046)**	**(0.044)**	(0.954)	(0.935)
RNN	2.063	1.686	1.269	2.160	-1.148	-1.136	-1.173	-1.512	-1.498	-1.467	3.931	4.119
	(0.976)	(0.949)	(0.893)	(0.980)	(0.130)	(0.133)	(0.125)	(0.071)	(0.073)	(0.077)	(1.000)	(1.000)
SVR-LIN	-1.069	-1.671	**-1.782**	**-1.706**	**-1.806**	**-1.801**	**-1.749**	**-3.096**	**-2.872**	**-2.915**	-0.812	-0.948
	(0.147)	(0.053)	**(0.043)**	**(0.049)**	**(0.041)**	**(0.041)**	**(0.045)**	**(0.002)**	**(0.004)**	**(0.003)**	(0.212)	(0.175)
SVR-POLY	-0.872	**-1.966**	**-2.032**	**-1.747**	**-1.712**	**-1.705**	-1.663	**-2.854**	**-2.680**	**-2.711**	0.328	0.249
	(0.195)	**(0.029)**	**(0.026)**	**(0.046)**	**(0.049)**	**(0.049)**	(0.054)	**(0.004)**	**(0.006)**	**(0.006)**	(0.627)	(0.598)
SVR-RBF	-1.139	-0.730	-0.986	-1.347	-1.637	-1.625	-1.563	**-2.919**	**-2.829**	**-2.754**	0.608	0.792
	(0.132)	(0.236)	(0.166)	(0.094)	(0.056)	(0.057)	(0.064)	**(0.003)**	**(0.004)**	**(0.005)**	(0.726)	(0.783)
SVR-ANOVA	-1.523	**-1.949**	**-2.029**	**-2.445**	**-1.791**	**-1.784**	**-1.724**	**-3.086**	**-2.907**	**-2.910**	-0.658	-1.598
	(0.069)	**(0.031)**	**(0.026)**	**(0.010)**	**(0.042)**	**(0.042)**	**(0.048)**	**(0.002)**	**(0.003)**	**(0.003)**	(0.258)	(0.060)
AR+SVR-POLY	-0.613	-1.581	**-1.718**	-1.097	-1.624	-1.613	-1.592	**-2.729**	**-2.541**	**-2.574**	1.044	2.223
	(0.272)	(0.062)	**(0.048)**	(0.141)	(0.058)	(0.059)	(0.061)	**(0.005)**	**(0.008)**	**(0.008)**	(0.847)	(0.983)
AR+SVR-RBF	-0.009	-0.282	-0.537	-0.992	-1.539	-1.525	-1.495	**-2.600**	**-2.478**	**-2.430**	1.016	1.511
	(0.497)	(0.390)	(0.298)	(0.165)	(0.067)	(0.069)	(0.073)	**(0.007)**	**(0.010)**	**(0.011)**	(0.841)	(0.929)
AR+SVR-ANOVA	-0.511	-1.401	-1.589	-1.008	-1.624	-1.614	-1.594	**-2.747**	**-2.548**	**-2.588**	1.318	3.057
	(0.307)	(0.086)	(0.061)	(0.161)	(0.058)	(0.059)	(0.061)	**(0.005)**	**(0.008)**	**(0.007)**	(0.901)	(0.998)
AR+FFNN	0.575	0.422	0.086	0.137	-1.378	-1.368	-1.397	**-1.967**	**-1.887**	**-1.939**	1.905	2.016
	(0.715)	(0.662)	(0.534)	(0.554)	(0.089)	(0.091)	(0.086)	**(0.029)**	**(0.035)**	**(0.031)**	(0.967)	(0.973)
AR+RNN	2.622	2.507	2.270	2.283	-0.356	-0.340	-0.501	0.239	0.131	0.139	3.503	3.601
	(0.993)	(0.991)	(0.985)	(0.985)	(0.362)	(0.368)	(0.310)	(0.594)	(0.552)	(0.555)	(0.999)	(0.999)
Ave. BM	-0.160	-1.057	-1.533	**-2.095**	-1.535	-1.525	-1.495	**-2.498**	**-2.419**	**-2.386**	0.935	1.142
	(0.437)	(0.150)	(0.068)	**(0.022)**	(0.068)	(0.069)	(0.073)	**(0.009)**	**(0.011)**	**(0.012)**	(0.821)	(0.869)
Ave. Linear	1.038	0.849	0.623	0.797	**-1.790**	**-1.779**	-1.653	**-3.638**	**-3.036**	**-3.492**	1.715	1.631
	(0.846)	(0.798)	(0.731)	(0.784)	**(0.042)**	**(0.043)**	(0.055)	**(0.001)**	**(0.003)**	**(0.001)**	(0.952)	(0.943)
Ave. Local	1.759	0.660	0.289	0.548	-1.381	-1.367	-1.347	**-2.306**	**-2.295**	**-2.211**	1.647	2.111
	(0.955)	(0.743)	(0.613)	(0.706)	(0.089)	(0.091)	(0.094)	**(0.014)**	**(0.015)**	**(0.018)**	(0.945)	(0.978)
Ave. Non-linear	-0.451	-0.891	-1.096	-1.129	-1.689	-1.683	-1.647	**-2.779**	**-2.593**	**-2.632**	1.553	1.372
	(0.328)	(0.190)	(0.141)	(0.134)	(0.051)	(0.052)	(0.055)	**(0.005)**	**(0.007)**	**(0.007)**	(0.934)	(0.910)
Ave. AR+	0.227	-0.253	-0.710	-0.427	-1.486	-1.475	-1.472	**-2.364**	**-2.237**	**-2.265**	1.989	4.499
	(0.589)	(0.401)	(0.242)	(0.336)	(0.074)	(0.075)	(0.076)	**(0.013)**	**(0.017)**	**(0.016)**	(0.972)	(1.000)
Tot. Ave.	0.046	-0.290	-0.583	-0.764	**-1.726**	**-1.717**	-1.648	**-3.414**	**-3.094**	**-3.115**	1.477	1.657
	(0.518)	(0.387)	(0.282)	(0.226)	**(0.047)**	**(0.048)**	(0.055)	**(0.001)**	**(0.002)**	**(0.002)**	(0.925)	(0.946)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.23: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 2$. $N = 30$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	0.959	-0.530	-1.246	-1.198	**-2.943**	**-1.744**	1.362	-0.521	**-2.063**	1.069	0.872	1.139
	(0.827)	(0.300)	(0.111)	(0.120)	**(0.003)**	**(0.046)**	(0.908)	(0.303)	**(0.024)**	(0.853)	(0.805)	(0.868)
RW	1.303	-0.459	-1.231	-1.192	**-1.953**	-1.327	1.114	-0.377	-1.686	1.671	1.966	0.730
	(0.899)	(0.325)	(0.114)	(0.121)	**(0.030)**	(0.097)	(0.863)	(0.354)	(0.051)	(0.947)	(0.971)	(0.764)
DDD	1.454	-0.184	-1.179	-1.154	-1.694	-0.994	1.306	-0.145	-1.269	1.782	2.032	0.986
	(0.922)	(0.428)	(0.124)	(0.129)	(0.051)	(0.164)	(0.899)	(0.443)	(0.107)	(0.957)	(0.974)	(0.834)
VAR(4)	1.798	-0.231	-1.216	-1.171	**-2.928**	**-1.871**	4.908	-0.202	**-2.160**	1.706	1.747	1.347
	(0.959)	(0.410)	(0.117)	(0.126)	**(0.003)**	**(0.036)**	(1.000)	(0.420)	**(0.020)**	(0.951)	(0.954)	(0.906)
GETS	1.736	1.672	-0.297	-0.691	0.885	1.194	1.667	1.392	1.148	1.806	1.712	1.637
	(0.953)	(0.947)	(0.384)	(0.248)	(0.808)	(0.879)	(0.947)	(0.913)	(0.870)	(0.959)	(0.951)	(0.944)
GETS-IIS	1.729	1.670	-0.331	-0.713	0.865	1.179	1.657	1.384	1.136	1.801	1.705	1.625
	(0.953)	(0.947)	(0.371)	(0.241)	(0.803)	(0.876)	(0.946)	(0.912)	(0.867)	(0.959)	(0.951)	(0.943)
GETS-SIS	1.682	1.652	0.037	-0.490	0.928	1.193	1.603	1.412	1.173	1.749	1.663	1.563
	(0.948)	(0.945)	(0.515)	(0.314)	(0.819)	(0.879)	(0.940)	(0.916)	(0.875)	(0.955)	(0.946)	(0.936)
GETS-DDD	3.003	2.422	-0.689	-0.813	0.850	1.716	2.855	1.797	1.512	3.096	2.854	2.919
	(0.997)	(0.989)	(0.248)	(0.211)	(0.799)	(0.952)	(0.996)	(0.959)	(0.929)	(0.998)	(0.996)	(0.997)
GETS-IIS-DDD	2.808	2.211	-0.650	-0.785	1.023	1.767	2.739	1.738	1.498	2.872	2.680	2.829
	(0.996)	(0.982)	(0.260)	(0.220)	(0.843)	(0.956)	(0.995)	(0.954)	(0.927)	(0.996)	(0.994)	(0.996)
GETS-SIS-DDD	2.856	2.377	-0.654	-0.791	0.929	1.677	2.726	1.760	1.467	2.915	2.711	2.754
	(0.996)	(0.988)	(0.259)	(0.218)	(0.820)	(0.948)	(0.995)	(0.956)	(0.923)	(0.997)	(0.994)	(0.995)
Ridge, CV	-0.291	**-2.015**	-1.380	-1.311	**-2.380**	**-2.094**	-0.391	**-1.742**	**-3.931**	0.812	-0.328	-0.608
	(0.386)	**(0.027)**	(0.089)	(0.100)	**(0.012)**	**(0.023)**	(0.349)	**(0.046)**	**(0.000)**	(0.788)	(0.373)	(0.274)
Lasso, CV	-0.939	-1.573	-1.355	-1.288	**-2.692**	**-2.365**	-0.539	-1.562	**-4.119**	0.948	-0.249	-0.792
	(0.178)	(0.063)	(0.093)	(0.104)	**(0.006)**	**(0.012)**	(0.297)	(0.065)	**(0.000)**	(0.825)	(0.402)	(0.217)
ELNET, CV	-	-1.548	-1.350	-1.285	**-2.658**	**-2.321**	-0.449	-1.525	**-4.167**	1.130	-0.138	-0.730
	-	(0.066)	(0.094)	(0.105)	**(0.006)**	**(0.014)**	(0.328)	(0.069)	**(0.000)**	(0.866)	(0.446)	(0.236)
Ridge, AIC	1.548	-	-1.240	-1.217	-1.245	-0.576	1.062	0.021	-1.215	2.061	1.546	0.807
	(0.934)	-	(0.112)	(0.117)	(0.112)	(0.285)	(0.851)	(0.508)	(0.117)	(0.976)	(0.933)	(0.787)
Lasso, AIC	1.350	1.240	-	-1.021	0.788	1.016	1.313	1.103	0.947	1.403	1.351	1.297
	(0.906)	(0.888)	-	(0.158)	(0.781)	(0.841)	(0.900)	(0.860)	(0.824)	(0.914)	(0.906)	(0.898)
ELNET, AIC	1.285	1.217	1.021	-	0.863	1.032	1.253	1.111	0.991	1.326	1.286	1.236
	(0.895)	(0.883)	(0.842)	-	(0.802)	(0.845)	(0.890)	(0.862)	(0.835)	(0.902)	(0.896)	(0.887)
k-NN	2.658	1.245	-0.788	-0.863	-	1.910	3.007	1.343	0.732	2.691	2.485	3.399
	(0.994)	(0.888)	(0.219)	(0.198)	-	(0.967)	(0.997)	(0.905)	(0.765)	(0.994)	(0.991)	(0.999)
wk-NN	2.321	0.576	-1.016	-1.032	**-1.910**	-	2.396	0.615	-0.433	2.467	2.156	2.275
	(0.986)	(0.715)	(0.159)	(0.155)	**(0.033)**	-	(0.988)	(0.728)	(0.334)	(0.990)	(0.980)	(0.985)
RF	0.449	-1.062	-1.313	-1.253	**-3.007**	**-2.396**	-	-1.108	**-3.271**	0.749	0.267	-0.969
	(0.672)	(0.149)	(0.100)	(0.110)	**(0.003)**	**(0.012)**	-	(0.139)	**(0.001)**	(0.770)	(0.604)	(0.170)
FFNN	1.525	-0.021	-1.103	-1.111	-1.343	-0.615	1.108	-	-1.164	2.022	1.420	0.841
	(0.931)	(0.492)	(0.140)	(0.138)	(0.095)	(0.272)	(0.861)	-	(0.127)	(0.974)	(0.917)	(0.796)
RNN	4.167	1.215	-0.947	-0.991	-0.732	0.433	3.271	1.164	-	4.479	3.375	2.714
	(1.000)	(0.883)	(0.176)	(0.165)	(0.235)	(0.666)	(0.999)	(0.873)	-	(1.000)	(0.999)	(0.994)
SVR-LIN	-1.130	**-2.061**	-1.403	-1.326	**-2.691**	**-2.467**	-0.749	**-2.022**	**-4.479**	-	-0.890	-0.923
	(0.134)	**(0.024)**	(0.086)	(0.098)	**(0.006)**	**(0.010)**	(0.230)	**(0.026)**	**(0.000)**	-	(0.190)	(0.182)
SVR-POLY	0.138	-1.546	-1.351	-1.286	**-2.485**	**-2.156**	-0.267	-1.420	**-3.375**	0.890	-	-0.587
	(0.554)	(0.067)	(0.094)	(0.104)	**(0.009)**	**(0.020)**	(0.396)	(0.083)	**(0.001)**	(0.810)	-	(0.281)
SVR-RBF	0.730	-0.807	-1.297	-1.236	**-3.399**	**-2.275**	0.969	-0.841	**-2.714**	0.923	0.587	-
	(0.764)	(0.213)	(0.102)	(0.113)	**(0.001)**	**(0.015)**	(0.830)	(0.204)	**(0.006)**	(0.818)	(0.719)	-
SVR-ANOVA	**-1.748**	**-1.766**	-1.408	-1.326	**-3.054**	**-2.872**	-1.579	**-1.898**	**-4.595**	-0.449	-1.167	-1.501
	(0.046)	**(0.044)**	(0.085)	(0.098)	**(0.002)**	**(0.004)**	(0.063)	**(0.034)**	**(0.000)**	(0.329)	(0.126)	(0.072)
AR+SVR-POLY	1.976	-1.103	-1.284	-1.234	**-2.394**	**-1.966**	0.597	-1.116	**-2.979**	1.493	0.533	-0.174
	(0.971)	(0.139)	(0.105)	(0.114)	**(0.012)**	**(0.029)**	(0.723)	(0.137)	**(0.003)**	(0.927)	(0.701)	(0.431)
AR+SVR-RBF	1.434	-0.604	-1.238	-1.194	**-2.799**	**-1.927**	0.890	-0.621	**-2.246**	1.388	1.834	0.506
	(0.919)	(0.275)	(0.113)	(0.121)	**(0.005)**	**(0.032)**	(0.810)	(0.270)	**(0.016)**	(0.912)	(0.962)	(0.692)
AR+SVR-ANOVA	2.726	-1.117	-1.281	-1.232	**-2.341**	**-1.898**	0.643	-1.103	**-3.008**	1.785	0.593	-0.086
	(0.995)	(0.137)	(0.105)	(0.114)	**(0.013)**	**(0.034)**	(0.737)	(0.140)	**(0.003)**	(0.958)	(0.721)	(0.466)
AR+FFNN	1.943	-0.129	-1.105	-1.104	-1.544	-0.732	1.405	-0.126	-1.168	2.171	1.862	0.996
	(0.969)	(0.449)	(0.139)	(0.139)	(0.067)	(0.235)	(0.915)	(0.450)	(0.126)	(0.981)	(0.964)	(0.836)
AR+RNN	3.596	1.988	-0.401	-0.577	0.767	1.585	3.292	2.237	1.573	3.702	3.383	2.872
	(0.999)	(0.972)	(0.346)	(0.284)	(0.775)	(0.938)	(0.999)	(0.983)	(0.937)	(1.000)	(0.999)	(0.996)
Ave. BM	1.061	-0.691	-1.247	-1.203	**-2.366**	**-1.745**	1.011	-0.652	**-2.152**	1.332	1.455	0.407
	(0.851)	(0.248)	(0.111)	(0.119)	**(0.012)**	**(0.046)**	(0.840)	(0.260)	**(0.020)**	(0.903)	(0.922)	(0.656)
Ave. Linear	1.617	0.842	-1.221	-1.193	-0.863	-0.025	1.399	0.504	-0.349	1.799	1.519	1.270
	(0.942)	(0.797)	(0.116)	(0.121)	(0.198)	(0.490)	(0.914)	(0.691)	(0.365)	(0.959)	(0.930)	(0.893)
Ave. Local	2.051	0.031	-1.126	-1.110	**-3.095**	-1.591	2.725	0.049	-1.398	2.073	1.793	3.034
	(0.975)	(0.512)	(0.135)	(0.138)	**(0.002)**	(0.061)	(0.995)	(0.519)	(0.086)	(0.976)	(0.958)	(0.997)
Ave. Non-linear	1.237	-1.421	-1.317	-1.262	**-2.365**	**-1.930**	0.293	-1.347	**-3.800**	3.098	0.936	-0.145
	(0.887)	(0.083)	(0.099)	(0.108)	**(0.012)**	**(0.032)**	(0.614)	(0.094)	**(0.000)**	(0.998)	(0.822)	(0.443)
Ave. AR+	4.223	-0.576	-1.192	-1.166	**-2.102**	-1.466	2.737	-0.616	**-2.234**	2.644	4.478	0.874
	(1.000)	(0.284)	(0.121)	(0.127)	**(0.022)**	(0.077)	(0.995)	(0.271)	**(0.017)**	(0.993)	(1.000)	(0.805)
Tot. Ave.	1.606	-0.934	-1.321	-1.258	**-2.573**	**-1.833**	1.060	-0.707	**-3.593**	1.964	1.247	0.578
	(0.940)	(0.179)	(0.098)	(0.109)	**(0.008)**	**(0.039)**	(0.851)	(0.242)	**(0.001)**	(0.970)	(0.889)	(0.716)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.24: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 2$. $N = 30$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	1.523	0.613	0.009	0.511	-0.575	**-2.622**	0.160	-1.038	**-1.759**	0.451	-0.227	-0.046
	(0.931)	(0.728)	(0.503)	(0.693)	(0.285)	**(0.007)**	(0.563)	(0.154)	**(0.045)**	(0.672)	(0.411)	(0.482)
RW	1.949	1.581	0.282	1.401	-0.422	**-2.507**	1.057	-0.849	-0.660	0.891	0.253	0.290
	(0.969)	(0.938)	(0.610)	(0.914)	(0.338)	**(0.009)**	(0.850)	(0.202)	(0.257)	(0.810)	(0.599)	(0.613)
DDD	2.029	1.718	0.537	1.589	-0.086	**-2.270**	1.533	-0.623	-0.289	1.096	0.710	0.583
	(0.974)	(0.952)	(0.702)	(0.939)	(0.466)	**(0.015)**	(0.932)	(0.269)	(0.387)	(0.859)	(0.758)	(0.718)
VAR(4)	2.445	1.097	0.992	1.008	-0.137	**-2.283**	2.095	-0.797	-0.548	1.129	0.427	0.764
	(0.990)	(0.859)	(0.835)	(0.839)	(0.446)	**(0.015)**	(0.978)	(0.216)	(0.294)	(0.866)	(0.664)	(0.774)
GETS	1.791	1.624	1.539	1.624	1.378	0.356	1.535	1.790	1.381	1.689	1.486	1.726
	(0.958)	(0.942)	(0.933)	(0.942)	(0.911)	(0.638)	(0.932)	(0.958)	(0.911)	(0.949)	(0.926)	(0.953)
GETS-IIS	1.784	1.613	1.525	1.614	1.368	0.340	1.525	1.779	1.367	1.683	1.475	1.717
	(0.958)	(0.941)	(0.931)	(0.941)	(0.909)	(0.632)	(0.931)	(0.957)	(0.909)	(0.948)	(0.925)	(0.952)
GETS-SIS	1.724	1.592	1.495	1.594	1.397	0.501	1.495	1.653	1.347	1.647	1.472	1.648
	(0.952)	(0.939)	(0.927)	(0.939)	(0.914)	(0.690)	(0.927)	(0.945)	(0.906)	(0.945)	(0.924)	(0.945)
GETS-DDD	3.086	2.729	2.600	2.747	1.967	-0.239	2.498	3.638	2.306	2.779	2.364	3.414
	(0.998)	(0.995)	(0.993)	(0.995)	(0.971)	(0.406)	(0.991)	(0.999)	(0.986)	(0.995)	(0.987)	(0.999)
GETS-IIS-DDD	2.907	2.541	2.478	2.548	1.887	-0.131	2.419	3.036	2.295	2.593	2.237	3.094
	(0.997)	(0.992)	(0.990)	(0.992)	(0.965)	(0.448)	(0.989)	(0.997)	(0.985)	(0.993)	(0.983)	(0.998)
GETS-SIS-DDD	2.910	2.574	2.430	2.588	1.939	-0.139	2.386	3.492	2.211	2.632	2.265	3.115
	(0.997)	(0.992)	(0.989)	(0.993)	(0.969)	(0.445)	(0.988)	(0.999)	(0.982)	(0.993)	(0.984)	(0.998)
Ridge, CV	0.658	-1.044	-1.016	-1.318	**-1.905**	**-3.503**	-0.935	**-1.715**	-1.647	-1.553	**-1.989**	-1.477
	(0.742)	(0.153)	(0.159)	(0.099)	**(0.033)**	**(0.001)**	(0.179)	**(0.048)**	(0.055)	(0.066)	**(0.028)**	(0.075)
Lasso, CV	1.598	**-2.223**	-1.511	**-3.057**	**-2.016**	**-3.601**	-1.142	-1.631	**-2.111**	-1.372	**-4.499**	-1.657
	(0.940)	**(0.017)**	(0.071)	**(0.002)**	**(0.027)**	**(0.001)**	(0.131)	(0.057)	**(0.022)**	(0.090)	**(0.000)**	(0.054)
ELNET, CV	1.748	**-1.976**	-1.434	**-2.726**	**-1.943**	**-3.596**	-1.061	-1.617	**-2.051**	-1.237	**-4.223**	-1.606
	(0.954)	**(0.029)**	(0.081)	**(0.005)**	**(0.031)**	**(0.001)**	(0.149)	(0.058)	**(0.025)**	(0.113)	**(0.000)**	(0.060)
Ridge, AIC	1.766	1.103	0.604	1.117	0.129	**-1.988**	0.691	-0.842	-0.031	1.421	0.576	0.934
	(0.956)	(0.861)	(0.725)	(0.863)	(0.551)	**(0.028)**	(0.752)	(0.203)	(0.488)	(0.917)	(0.716)	(0.821)
Lasso, AIC	1.408	1.284	1.238	1.281	1.105	0.401	1.247	1.221	1.126	1.317	1.192	1.321
	(0.915)	(0.895)	(0.887)	(0.895)	(0.861)	(0.654)	(0.889)	(0.884)	(0.865)	(0.901)	(0.879)	(0.902)
ELNET, AIC	1.326	1.234	1.194	1.232	1.104	0.577	1.203	1.193	1.110	1.262	1.166	1.258
	(0.902)	(0.886)	(0.879)	(0.886)	(0.861)	(0.716)	(0.881)	(0.879)	(0.862)	(0.892)	(0.873)	(0.891)
k-NN	3.054	2.394	2.799	2.341	1.544	-0.767	2.366	0.863	3.095	2.365	2.102	2.573
	(0.998)	(0.988)	(0.995)	(0.987)	(0.933)	(0.225)	(0.988)	(0.802)	(0.998)	(0.988)	(0.978)	(0.992)
wk-NN	2.872	1.966	1.927	1.898	0.732	-1.585	1.745	0.025	1.591	1.930	1.466	1.833
	(0.996)	(0.971)	(0.968)	(0.966)	(0.765)	(0.062)	(0.954)	(0.510)	(0.939)	(0.968)	(0.923)	(0.961)
RF	1.579	-0.597	-0.890	-0.643	-1.405	**-3.292**	-1.011	-1.399	**-2.725**	-0.293	**-2.737**	-1.060
	(0.937)	(0.277)	(0.190)	(0.263)	(0.085)	**(0.001)**	(0.160)	(0.086)	**(0.005)**	(0.386)	**(0.005)**	(0.149)
FFNN	1.898	1.116	0.621	1.103	0.126	**-2.237**	0.652	-0.504	-0.049	1.347	0.616	0.707
	(0.966)	(0.863)	(0.730)	(0.860)	(0.550)	**(0.017)**	(0.740)	(0.309)	(0.481)	(0.906)	(0.729)	(0.758)
RNN	4.595	2.979	2.246	3.008	1.168	-1.573	2.152	0.349	1.398	3.800	2.234	3.593
	(1.000)	(0.997)	(0.984)	(0.997)	(0.874)	(0.063)	(0.980)	(0.635)	(0.914)	(1.000)	(0.983)	(0.999)
SVR-LIN	0.449	-1.493	-1.388	**-1.785**	**-2.171**	**-3.702**	-1.332	**-1.799**	**-2.073**	**-3.098**	**-2.644**	**-1.964**
	(0.671)	(0.073)	(0.088)	**(0.042)**	**(0.019)**	**(0.000)**	(0.097)	**(0.041)**	**(0.024)**	**(0.002)**	**(0.007)**	**(0.030)**
SVR-POLY	1.167	-0.533	**-1.834**	-0.593	**-1.862**	**-3.383**	-1.455	-1.519	**-1.793**	-0.936	**-4.478**	-1.247
	(0.874)	(0.299)	**(0.038)**	(0.279)	**(0.036)**	**(0.001)**	(0.078)	(0.070)	**(0.042)**	(0.178)	**(0.000)**	(0.111)
SVR-RBF	1.501	0.174	-0.506	0.086	-0.996	**-2.872**	-0.407	-1.270	**-3.034**	0.145	-0.874	-0.578
	(0.928)	(0.569)	(0.308)	(0.534)	(0.164)	**(0.004)**	(0.344)	(0.107)	**(0.003)**	(0.557)	(0.195)	(0.284)
SVR-ANOVA	-	**-2.151**	**-2.269**	**-2.282**	**-2.226**	**-3.810**	**-1.859**	**-1.769**	**-2.780**	**-2.414**	**-3.829**	**-2.169**
	-	**(0.020)**	**(0.015)**	**(0.015)**	**(0.017)**	**(0.000)**	**(0.037)**	**(0.044)**	**(0.005)**	**(0.011)**	**(0.000)**	**(0.019)**
AR+SVR-POLY	2.151	-	-0.804	-0.993	-1.565	**-3.239**	-1.324	-1.267	-1.659	0.020	**-3.184**	-0.657
	(0.980)	-	(0.214)	(0.164)	(0.064)	**(0.002)**	(0.098)	(0.108)	(0.054)	(0.508)	**(0.002)**	(0.258)
AR+SVR-RBF	2.269	0.804	-	0.661	-0.737	**-2.728**	0.104	-1.000	**-2.453**	0.639	-0.324	-0.057
	(0.985)	(0.786)	-	(0.743)	(0.234)	**(0.005)**	(0.541)	(0.163)	**(0.010)**	(0.736)	(0.374)	(0.477)
AR+SVR-ANOVA	2.282	0.993	-0.661	-	-1.585	**-3.217**	-0.886	-1.268	-1.547	0.161	**-3.084**	-0.613
	(0.985)	(0.836)	(0.257)	-	(0.062)	**(0.002)**	(0.191)	(0.108)	(0.066)	(0.563)	**(0.002)**	(0.272)
AR+FFNN	2.226	1.565	0.737	1.585	-	**-2.331**	0.846	-0.554	-0.173	1.443	0.860	0.632
	(0.983)	(0.936)	(0.766)	(0.938)	-	**(0.013)**	(0.798)	(0.292)	(0.432)	(0.920)	(0.802)	(0.734)
AR+RNN	3.810	3.239	2.728	3.217	2.331	-	2.844	1.284	2.123	3.103	3.011	2.610
	(1.000)	(0.998)	(0.995)	(0.998)	(0.987)	-	(0.996)	(0.895)	(0.979)	(0.998)	(0.997)	(0.993)
Ave. BM	1.859	1.324	-0.104	0.886	-0.846	**-2.844**	-	-1.034	-1.321	0.469	-0.964	-0.168
	(0.963)	(0.902)	(0.459)	(0.809)	(0.202)	**(0.004)**	-	(0.155)	(0.098)	(0.679)	(0.171)	(0.434)
Ave. Linear	1.769	1.267	1.000	1.268	0.554	-1.284	1.034	-	0.511	1.439	0.895	1.529
	(0.956)	(0.892)	(0.837)	(0.892)	(0.708)	(0.105)	(0.845)	-	(0.693)	(0.920)	(0.811)	(0.931)
Ave. Local	2.780	1.659	2.453	1.547	0.173	**-2.123**	1.321	-0.511	-	1.452	0.980	1.222
	(0.995)	(0.946)	(0.990)	(0.934)	(0.568)	**(0.021)**	(0.902)	(0.307)	-	(0.921)	(0.832)	(0.884)
Ave. Non-linear	2.414	-0.020	-0.639	-0.161	-1.443	**-3.103**	-0.469	-1.439	-1.452	-	-1.337	-0.936
	(0.989)	(0.492)	(0.264)	(0.437)	(0.080)	**(0.002)**	(0.321)	(0.080)	(0.079)	-	(0.096)	(0.178)
Ave. AR+	3.829	3.184	0.324	3.084	-0.860	**-3.011**	0.964	-0.895	-0.980	1.337	-	0.164
	(1.000)	(0.998)	(0.626)	(0.998)	(0.198)	**(0.003)**	(0.829)	(0.189)	(0.168)	(0.904)	-	(0.565)
Tot. Ave.	2.169	0.657	0.057	0.613	-0.632	**-2.610**	0.168	-1.529	-1.222	0.936	-0.164	-
	(0.981)	(0.742)	(0.523)	(0.728)	(0.266)	**(0.007)**	(0.566)	(0.069)	(0.116)	(0.822)	(0.435)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.25: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 3$. $N = 29$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-1.204	**-1.786**	-0.873	-0.995	-1.016	-0.899	**-3.464**	**-3.044**	**-3.007**	0.199	-1.657
	-	(0.119)	**(0.042)**	(0.195)	(0.164)	(0.159)	(0.188)	**(0.001)**	**(0.003)**	**(0.003)**	(0.578)	(0.054)
RW	1.204	-	**-2.807**	-0.128	-0.592	-0.694	-0.558	**-3.739**	**-3.122**	**-3.357**	1.572	0.265
	(0.881)	-	**(0.004)**	(0.450)	(0.279)	(0.247)	(0.291)	**(0.000)**	**(0.002)**	**(0.001)**	(0.936)	(0.603)
DDD	1.786	2.807	-	0.353	-0.152	-0.287	-0.118	**-2.648**	**-2.276**	**-2.560**	1.991	0.540
	(0.958)	(0.996)	-	(0.637)	(0.440)	(0.388)	(0.454)	**(0.007)**	**(0.015)**	**(0.008)**	(0.972)	(0.703)
VAR(4)	0.873	0.128	-0.353	-	-0.407	-0.511	-0.357	**-3.561**	**-2.954**	**-2.897**	7.987	0.345
	(0.805)	(0.550)	(0.363)	-	(0.344)	(0.307)	(0.362)	**(0.001)**	**(0.003)**	**(0.004)**	(1.000)	(0.634)
GETS	0.995	0.592	0.152	0.407	-	-0.645	0.113	**-1.910**	**-2.054**	**-2.051**	1.464	0.826
	(0.836)	(0.721)	(0.560)	(0.656)	-	(0.262)	(0.545)	**(0.033)**	**(0.025)**	**(0.025)**	(0.923)	(0.792)
GETS-IIS	1.016	0.694	0.287	0.511	0.645	-	0.912	-1.679	**-1.886**	**-1.877**	1.432	0.924
	(0.841)	(0.753)	(0.612)	(0.693)	(0.738)	-	(0.815)	(0.052)	**(0.035)**	**(0.035)**	(0.918)	(0.818)
GETS-SIS	0.899	0.558	0.118	0.357	-0.113	-0.912	-	**-2.405**	**-2.720**	**-2.658**	1.329	0.786
	(0.812)	(0.709)	(0.546)	(0.638)	(0.455)	(0.185)	-	**(0.012)**	**(0.006)**	**(0.006)**	(0.903)	(0.781)
GETS-DDD	3.464	3.739	2.648	3.561	1.910	1.679	2.405	-	-0.252	-0.554	4.990	24.780
	(0.999)	(1.000)	(0.993)	(0.999)	(0.967)	(0.948)	(0.988)	-	(0.401)	(0.292)	(1.000)	(1.000)
GETS-IIS-DDD	3.044	3.122	2.276	2.954	2.054	1.886	2.720	0.252	-	-0.504	4.206	5.802
	(0.997)	(0.998)	(0.985)	(0.997)	(0.975)	(0.965)	(0.994)	(0.599)	-	(0.309)	(1.000)	(1.000)
GETS-SIS-DDD	3.007	3.357	2.560	2.897	2.051	1.877	2.658	0.554	0.504	-	4.043	5.108
	(0.997)	(0.999)	(0.992)	(0.996)	(0.975)	(0.965)	(0.994)	(0.708)	(0.691)	-	(1.000)	(1.000)
Ridge, CV	-0.199	-1.572	**-1.991**	**-7.987**	-1.464	-1.432	-1.329	**-4.990**	**-4.206**	**-4.043**	-	**-2.913**
	(0.422)	(0.064)	**(0.028)**	**(0.000)**	(0.077)	(0.082)	(0.097)	**(0.000)**	**(0.000)**	**(0.000)**	-	**(0.003)**
Lasso, CV	1.657	-0.265	-0.540	-0.345	-0.826	-0.924	-0.786	**-24.780**	**-5.802**	**-5.108**	2.913	-
	(0.946)	(0.397)	(0.297)	(0.366)	(0.208)	(0.182)	(0.219)	**(0.000)**	**(0.000)**	**(0.000)**	(0.997)	-
ELNET, CV	1.821	-0.238	-0.522	-0.325	-0.796	-0.894	-0.756	**-15.540**	**-5.504**	**-4.882**	2.887	0.644
	(0.960)	(0.407)	(0.303)	(0.374)	(0.216)	(0.189)	(0.228)	**(0.000)**	**(0.000)**	**(0.000)**	(0.996)	(0.738)
Ridge, AIC	-0.627	-1.178	**-8.846**	**-1.877**	**-1.800**	-1.654	-1.492	**-7.069**	**-5.675**	**-5.295**	-0.423	**-1.886**
	(0.268)	(0.124)	**(0.000)**	**(0.035)**	**(0.041)**	(0.055)	(0.073)	**(0.000)**	**(0.000)**	**(0.000)**	(0.338)	**(0.035)**
Lasso, AIC	1.044	1.037	0.989	0.994	0.970	0.984	1.039	0.725	0.727	0.721	1.084	1.029
	(0.847)	(0.846)	(0.834)	(0.836)	(0.830)	(0.833)	(0.846)	(0.763)	(0.763)	(0.762)	(0.856)	(0.844)
ELNET, AIC	1.090	1.088	1.030	1.024	1.026	1.054	1.115	0.722	0.727	0.717	1.145	1.072
	(0.858)	(0.857)	(0.844)	(0.843)	(0.843)	(0.849)	(0.863)	(0.762)	(0.763)	(0.760)	(0.869)	(0.854)
k-NN	1.226	0.638	0.143	0.539	-0.030	-0.160	0.005	-1.545	-1.468	-1.471	1.356	0.781
	(0.885)	(0.736)	(0.557)	(0.703)	(0.488)	(0.437)	(0.502)	(0.067)	(0.077)	(0.076)	(0.907)	(0.779)
wk-NN	0.981	0.209	-0.347	0.091	-0.382	-0.475	-0.321	**-2.643**	**-2.327**	**-2.292**	1.076	0.426
	(0.833)	(0.582)	(0.366)	(0.536)	(0.353)	(0.319)	(0.375)	**(0.007)**	**(0.014)**	**(0.015)**	(0.855)	(0.663)
RF	-0.748	**-1.783**	**-2.166**	**-2.220**	-1.533	-1.435	-1.325	**-4.367**	**-3.831**	**-3.724**	-1.046	**-1.704**
	(0.230)	**(0.043)**	**(0.019)**	**(0.017)**	(0.068)	(0.081)	(0.098)	**(0.000)**	**(0.000)**	**(0.000)**	(0.152)	**(0.050)**
FFNN	-0.501	-1.496	**-1.860**	-1.150	**-3.076**	**-2.280**	**-1.947**	**-4.357**	**-4.260**	**-4.135**	-0.606	-0.977
	(0.310)	(0.073)	**(0.037)**	(0.130)	**(0.002)**	**(0.015)**	**(0.031)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.275)	(0.169)
RNN	1.451	0.116	**-12.749**	0.010	-0.832	-0.859	-0.593	**-5.292**	**-4.755**	**-4.109**	0.920	1.118
	(0.921)	(0.546)	**(0.000)**	(0.504)	(0.206)	(0.199)	(0.279)	**(0.000)**	**(0.000)**	**(0.000)**	(0.817)	(0.863)
SVR-LIN	-1.320	**-2.554**	**-2.771**	**-2.072**	**-2.816**	**-2.275**	**-2.086**	**-4.516**	**-4.252**	**-4.177**	**-1.705**	**-1.811**
	(0.099)	**(0.008)**	**(0.005)**	**(0.024)**	**(0.004)**	**(0.015)**	**(0.023)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.050)**	**(0.040)**
SVR-POLY	-1.284	**-2.432**	**-2.618**	**-2.063**	**-2.710**	**-2.206**	**-2.069**	**-4.465**	**-4.172**	**-4.078**	-1.681	**-1.765**
	(0.105)	**(0.011)**	**(0.007)**	**(0.024)**	**(0.006)**	**(0.018)**	**(0.024)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.052)	**(0.044)**
SVR-RBF	-1.303	**-2.323**	**-2.638**	**-2.687**	**-1.757**	-1.592	-1.499	**-4.422**	**-3.896**	**-3.805**	-1.385	**-1.844**
	(0.102)	**(0.014)**	**(0.007)**	**(0.006)**	**(0.045)**	(0.061)	(0.073)	**(0.000)**	**(0.000)**	**(0.000)**	(0.089)	**(0.038)**
SVR-ANOVA	0.629	0.494	0.018	0.237	-0.206	-0.772	-0.234	**-3.449**	**-4.828**	**-4.379**	0.812	0.482
	(0.733)	(0.687)	(0.507)	(0.593)	(0.419)	(0.223)	(0.408)	**(0.001)**	**(0.000)**	**(0.000)**	(0.788)	(0.683)
AR+SVR-POLY	0.809	0.407	-0.340	0.193	-0.462	-0.619	-0.460	**-3.947**	**-3.451**	**-3.887**	1.048	0.576
	(0.787)	(0.656)	(0.368)	(0.576)	(0.324)	(0.270)	(0.325)	**(0.000)**	**(0.001)**	**(0.000)**	(0.848)	(0.715)
AR+SVR-RBF	0.763	-0.633	-1.571	-0.749	-0.942	-0.946	-0.817	**-4.420**	**-3.620**	**-3.565**	0.973	-0.121
	(0.774)	(0.266)	(0.064)	(0.230)	(0.177)	(0.176)	(0.211)	**(0.000)**	**(0.001)**	**(0.001)**	(0.831)	(0.452)
AR+SVR-ANOVA	0.775	-0.354	-0.990	-0.533	-0.883	-0.913	-0.726	**-3.514**	**-3.175**	**-3.178**	1.115	0.052
	(0.778)	(0.363)	(0.165)	(0.299)	(0.192)	(0.184)	(0.237)	**(0.001)**	**(0.002)**	**(0.002)**	(0.863)	(0.520)
AR+FFNN	-0.155	-1.111	-1.570	-0.945	**-2.337**	**-1.800**	-1.538	**-4.457**	**-4.241**	**-4.173**	-0.110	-0.654
	(0.439)	(0.138)	(0.064)	(0.176)	**(0.013)**	**(0.041)**	(0.068)	**(0.000)**	**(0.000)**	**(0.000)**	(0.457)	(0.259)
AR+RNN	2.277	1.889	1.696	1.955	1.437	1.265	1.439	0.682	0.639	0.617	2.175	2.054
	(0.985)	(0.965)	(0.950)	(0.970)	(0.919)	(0.892)	(0.919)	(0.750)	(0.736)	(0.729)	(0.981)	(0.975)
Ave. BM	1.024	-1.403	**-2.076**	-0.618	-0.858	-0.902	-0.778	**-3.514**	**-3.064**	**-3.168**	1.263	-0.170
	(0.843)	(0.086)	**(0.024)**	(0.271)	(0.199)	(0.187)	(0.221)	**(0.001)**	**(0.002)**	**(0.002)**	(0.892)	(0.433)
Ave. Linear	0.376	-0.531	-1.168	-0.526	-1.533	-1.575	-1.512	**-7.235**	**-6.289**	**-5.887**	0.709	-0.108
	(0.645)	(0.300)	(0.126)	(0.302)	(0.068)	(0.063)	(0.071)	**(0.000)**	**(0.000)**	**(0.000)**	(0.758)	(0.458)
Ave. Local	0.533	-0.690	-1.270	-1.008	-0.955	-0.962	-0.821	**-3.764**	**-3.257**	**-3.169**	0.836	-0.263
	(0.701)	(0.248)	(0.107)	(0.161)	(0.174)	(0.172)	(0.209)	**(0.000)**	**(0.001)**	**(0.002)**	(0.795)	(0.397)
Ave. Non-linear	-1.129	**-2.340**	**-2.624**	**-2.057**	**-2.508**	**-2.056**	**-1.909**	**-4.479**	**-4.133**	**-4.039**	-1.464	-1.649
	(0.134)	**(0.013)**	**(0.007)**	**(0.025)**	**(0.009)**	**(0.025)**	**(0.033)**	**(0.000)**	**(0.000)**	**(0.000)**	(0.077)	(0.055)
Ave. AR+	0.826	-0.089	-0.846	-0.246	-0.742	-0.790	-0.624	**-3.543**	**-3.100**	**-3.137**	1.006	0.272
	(0.792)	(0.465)	(0.202)	(0.404)	(0.232)	(0.218)	(0.269)	**(0.001)**	**(0.002)**	**(0.002)**	(0.839)	(0.606)
Tot. Ave.	-1.097	**-2.903**	**-3.075**	**-2.228**	**-2.029**	**-1.786**	-1.686	**-4.855**	**-4.313**	**-4.200**	-1.538	**-1.892**
	(0.141)	**(0.004)**	**(0.002)**	**(0.017)**	**(0.026)**	**(0.042)**	(0.051)	**(0.000)**	**(0.000)**	**(0.000)**	(0.068)	**(0.034)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.26: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 3$. $N = 29$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	**-1.821**	0.627	-1.044	-1.090	-1.226	-0.981	0.748	0.501	-1.451	1.320	1.284	1.303
	(0.040)	(0.732)	(0.153)	(0.142)	(0.115)	(0.167)	(0.770)	(0.690)	(0.079)	(0.901)	(0.895)	(0.898)
RW	0.238	1.178	-1.037	-1.088	-0.638	-0.209	1.783	1.496	-0.116	2.554	2.432	2.323
	(0.593)	(0.876)	(0.154)	(0.143)	(0.264)	(0.418)	(0.957)	(0.927)	(0.454)	(0.992)	(0.989)	(0.986)
DDD	0.522	8.846	-0.989	-1.030	-0.143	0.347	2.166	1.860	12.749	2.771	2.618	2.638
	(0.697)	(1.000)	(0.166)	(0.156)	(0.443)	(0.634)	(0.981)	(0.963)	(1.000)	(0.995)	(0.993)	(0.993)
VAR(4)	0.325	1.877	-0.994	-1.024	-0.539	-0.091	2.220	1.150	-0.010	2.072	2.063	2.687
	(0.626)	(0.965)	(0.164)	(0.157)	(0.297)	(0.464)	(0.983)	(0.870)	(0.496)	(0.976)	(0.976)	(0.994)
GETS	0.796	1.800	-0.970	-1.026	0.030	0.382	1.533	3.076	0.832	2.816	2.710	1.757
	(0.784)	(0.959)	(0.170)	(0.157)	(0.512)	(0.647)	(0.932)	(0.998)	(0.794)	(0.996)	(0.994)	(0.955)
GETS-IIS	0.894	1.654	-0.984	-1.054	0.160	0.475	1.435	2.280	0.859	2.275	2.206	1.592
	(0.811)	(0.945)	(0.167)	(0.151)	(0.563)	(0.681)	(0.919)	(0.985)	(0.801)	(0.985)	(0.982)	(0.939)
GETS-SIS	0.756	1.492	-1.039	-1.115	-0.005	0.321	1.325	1.947	0.593	2.086	2.069	1.499
	(0.772)	(0.927)	(0.154)	(0.137)	(0.498)	(0.625)	(0.902)	(0.969)	(0.721)	(0.977)	(0.976)	(0.927)
GETS-DDD	15.540	7.069	-0.725	-0.722	1.545	2.643	4.367	4.357	5.292	4.516	4.465	4.422
	(1.000)	(1.000)	(0.237)	(0.238)	(0.933)	(0.993)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
GETS-IIS-DDD	5.504	5.675	-0.727	-0.727	1.468	2.327	3.831	4.260	4.755	4.252	4.172	3.896
	(1.000)	(1.000)	(0.237)	(0.237)	(0.923)	(0.986)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
GETS-SIS-DDD	4.882	5.295	-0.721	-0.717	1.471	2.292	3.724	4.135	4.109	4.177	4.078	3.805
	(1.000)	(1.000)	(0.238)	(0.240)	(0.924)	(0.985)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
Ridge, CV	**-2.887**	0.423	-1.084	-1.145	-1.356	-1.076	1.046	0.606	-0.920	1.705	1.681	1.385
	(0.004)	(0.662)	(0.144)	(0.131)	(0.093)	(0.145)	(0.848)	(0.725)	(0.183)	(0.950)	(0.948)	(0.911)
Lasso, CV	-0.644	1.886	-1.029	-1.072	-0.781	-0.426	1.704	0.977	-1.118	1.811	1.765	1.844
	(0.262)	(0.965)	(0.156)	(0.146)	(0.221)	(0.337)	(0.950)	(0.831)	(0.137)	(0.960)	(0.956)	(0.962)
ELNET, CV	-	1.868	-1.026	-1.067	-0.767	-0.410	1.762	0.991	-0.955	1.818	1.780	1.901
	-	(0.964)	(0.157)	(0.147)	(0.225)	(0.343)	(0.956)	(0.835)	(0.174)	(0.960)	(0.957)	(0.966)
Ridge, AIC	**-1.868**	-	-1.124	-1.190	-1.579	-1.396	-0.207	0.368	**-4.468**	2.062	1.855	0.738
	(0.036)	-	(0.135)	(0.122)	(0.063)	(0.087)	(0.419)	(0.642)	**(0.000)**	(0.976)	(0.963)	(0.767)
Lasso, AIC	1.026	1.124	-	0.722	0.875	0.930	1.087	1.147	1.009	1.185	1.174	1.113
	(0.843)	(0.865)	-	(0.762)	(0.806)	(0.820)	(0.857)	(0.869)	(0.839)	(0.877)	(0.875)	(0.862)
ELNET, AIC	1.067	1.190	-0.722	-	0.893	0.956	1.145	1.223	1.054	1.264	1.250	1.174
	(0.853)	(0.878)	(0.238)	-	(0.810)	(0.826)	(0.869)	(0.884)	(0.850)	(0.892)	(0.889)	(0.875)
k-NN	0.767	1.579	-0.875	-0.893	-	1.617	1.529	1.693	0.457	2.243	2.352	1.861
	(0.775)	(0.937)	(0.194)	(0.190)	-	(0.941)	(0.931)	(0.949)	(0.674)	(0.983)	(0.987)	(0.963)
wk-NN	0.410	1.396	-0.930	-0.956	-1.617	-	1.323	1.407	0.061	2.018	2.120	1.701
	(0.657)	(0.913)	(0.180)	(0.174)	(0.059)	-	(0.902)	(0.915)	(0.524)	(0.973)	(0.978)	(0.950)
RF	**-1.762**	0.207	-1.087	-1.145	-1.529	-1.323	-	0.344	-1.482	1.631	1.626	1.651
	(0.044)	(0.581)	(0.143)	(0.131)	(0.069)	(0.098)	-	(0.633)	(0.075)	(0.943)	(0.942)	(0.945)
FFNN	-0.991	-0.368	-1.147	-1.223	-1.693	-1.407	-0.344	-	**-3.707**	1.764	1.247	0.031
	(0.165)	(0.358)	(0.131)	(0.116)	(0.051)	(0.085)	(0.367)	-	**(0.000)**	(0.956)	(0.889)	(0.512)
RNN	0.955	4.468	-1.009	-1.054	-0.457	-0.061	1.482	3.707	-	3.074	2.881	19.330
	(0.826)	(1.000)	(0.161)	(0.150)	(0.326)	(0.476)	(0.925)	(1.000)	-	(0.998)	(0.996)	(1.000)
SVR-LIN	**-1.818**	**-2.062**	-1.185	-1.264	**-2.243**	**-2.018**	-1.631	**-1.764**	**-3.074**	-	-0.638	-1.166
	(0.040)	**(0.024)**	(0.123)	(0.108)	**(0.017)**	**(0.027)**	(0.057)	**(0.044)**	**(0.002)**	-	(0.264)	(0.127)
SVR-POLY	**-1.780**	**-1.855**	-1.174	-1.250	**-2.352**	**-2.120**	-1.626	-1.247	**-2.881**	0.638	-	-1.158
	(0.043)	**(0.037)**	(0.125)	(0.111)	**(0.013)**	**(0.022)**	(0.058)	(0.111)	**(0.004)**	(0.736)	-	(0.128)
SVR-RBF	**-1.901**	-0.738	-1.113	-1.174	**-1.861**	-1.701	-1.651	-0.031	**-19.330**	1.166	1.158	-
	(0.034)	(0.233)	(0.138)	(0.125)	**(0.037)**	(0.050)	(0.055)	(0.488)	**(0.000)**	(0.873)	(0.872)	-
SVR-ANOVA	0.460	0.970	-1.183	-1.284	-0.076	0.171	0.834	1.081	0.262	1.305	1.235	0.935
	(0.676)	(0.830)	(0.123)	(0.105)	(0.470)	(0.567)	(0.794)	(0.856)	(0.602)	(0.899)	(0.886)	(0.821)
AR+SVR-POLY	0.543	1.446	-1.047	-1.100	-0.249	0.073	1.195	1.497	0.257	1.962	1.905	1.485
	(0.704)	(0.920)	(0.152)	(0.140)	(0.403)	(0.529)	(0.879)	(0.927)	(0.601)	(0.970)	(0.966)	(0.926)
AR+SVR-RBF	-0.168	1.278	-1.019	-1.059	-0.787	-0.492	1.581	1.021	-0.885	2.006	2.024	2.314
	(0.434)	(0.894)	(0.159)	(0.149)	(0.219)	(0.313)	(0.937)	(0.842)	(0.192)	(0.973)	(0.974)	(0.986)
AR+SVR-ANOVA	-0.003	1.473	-1.016	-1.063	-0.671	-0.371	1.471	1.178	-0.669	2.156	2.050	1.878
	(0.499)	(0.924)	(0.159)	(0.149)	(0.254)	(0.357)	(0.924)	(0.876)	(0.254)	(0.980)	(0.975)	(0.965)
AR+FFNN	-0.671	0.370	-1.097	-1.163	-1.294	-0.997	0.199	3.388	**-2.975**	3.081	2.300	0.628
	(0.254)	(0.643)	(0.141)	(0.127)	(0.103)	(0.164)	(0.578)	(0.999)	**(0.003)**	(0.998)	(0.985)	(0.732)
AR+RNN	2.035	2.229	-0.388	-0.316	1.306	1.611	2.326	2.172	1.864	2.437	2.423	2.418
	(0.974)	(0.983)	(0.351)	(0.377)	(0.899)	(0.941)	(0.986)	(0.981)	(0.964)	(0.989)	(0.989)	(0.989)
Ave. BM	-0.200	0.934	-1.049	-1.101	-1.029	-0.704	1.974	1.053	-0.522	2.380	2.276	3.012
	(0.422)	(0.821)	(0.152)	(0.140)	(0.156)	(0.244)	(0.971)	(0.849)	(0.303)	(0.988)	(0.985)	(0.997)
Ave. Linear	-0.139	1.464	-1.106	-1.180	-0.776	-0.435	0.890	1.471	-0.677	2.128	2.050	1.229
	(0.445)	(0.923)	(0.139)	(0.124)	(0.222)	(0.333)	(0.809)	(0.924)	(0.252)	(0.979)	(0.975)	(0.885)
Ave. Local	-0.308	1.415	-1.018	-1.062	-1.583	-1.282	1.392	1.133	-1.017	2.332	2.633	2.261
	(0.380)	(0.916)	(0.159)	(0.149)	(0.062)	(0.105)	(0.913)	(0.867)	(0.159)	(0.986)	(0.993)	(0.984)
Ave. Non-linear	-1.668	-1.689	-1.151	-1.223	**-2.035**	**-1.785**	-1.417	-0.670	**-2.319**	2.177	2.086	-0.766
	(0.053)	(0.051)	(0.130)	(0.116)	**(0.026)**	**(0.043)**	(0.084)	(0.254)	**(0.014)**	(0.981)	(0.977)	(0.225)
Ave. AR+	0.232	1.343	-0.998	-1.036	-0.528	-0.207	1.347	1.235	-0.312	2.033	1.971	1.763
	(0.591)	(0.905)	(0.163)	(0.155)	(0.301)	(0.419)	(0.906)	(0.886)	(0.379)	(0.974)	(0.971)	(0.956)
Tot. Ave.	**-1.924**	-1.312	-1.141	-1.208	**-1.856**	**-1.712**	-1.435	-0.159	**-2.374**	1.330	1.348	-0.449
	(0.032)	(0.100)	(0.132)	(0.119)	**(0.037)**	**(0.049)**	(0.081)	(0.437)	**(0.012)**	(0.903)	(0.906)	(0.328)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.27: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 3$. $N = 29$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-0.629	-0.809	-0.763	-0.775	0.155	**-2.277**	-1.024	-0.376	-0.533	1.129	-0.826	1.097
	(0.267)	(0.213)	(0.226)	(0.222)	(0.561)	**(0.015)**	(0.157)	(0.355)	(0.299)	(0.866)	(0.208)	(0.859)
RW	-0.494	-0.407	0.633	0.354	1.111	**-1.889**	1.403	0.531	0.690	2.340	0.089	2.903
	(0.313)	(0.344)	(0.734)	(0.637)	(0.862)	**(0.035)**	(0.914)	(0.700)	(0.752)	(0.987)	(0.535)	(0.996)
DDD	-0.018	0.340	1.571	0.990	1.570	-1.696	2.076	1.168	1.270	2.624	0.846	3.075
	(0.493)	(0.632)	(0.936)	(0.835)	(0.936)	(0.050)	(0.976)	(0.874)	(0.893)	(0.993)	(0.798)	(0.998)
VAR(4)	-0.237	-0.193	0.749	0.533	0.945	**-1.955**	0.618	0.526	1.008	2.057	0.246	2.228
	(0.407)	(0.424)	(0.770)	(0.701)	(0.824)	**(0.030)**	(0.729)	(0.698)	(0.839)	(0.975)	(0.596)	(0.983)
GETS	0.206	0.462	0.942	0.883	2.337	-1.437	0.858	1.533	0.955	2.508	0.742	2.029
	(0.581)	(0.676)	(0.823)	(0.808)	(0.987)	(0.081)	(0.801)	(0.932)	(0.826)	(0.991)	(0.768)	(0.974)
GETS-IIS	0.772	0.619	0.946	0.913	1.800	-1.265	0.902	1.575	0.962	2.056	0.790	1.786
	(0.777)	(0.730)	(0.824)	(0.816)	(0.959)	(0.108)	(0.813)	(0.937)	(0.828)	(0.975)	(0.782)	(0.958)
GETS-SIS	0.234	0.460	0.817	0.726	1.538	-1.439	0.778	1.512	0.821	1.909	0.624	1.686
	(0.592)	(0.675)	(0.789)	(0.763)	(0.932)	(0.081)	(0.779)	(0.929)	(0.791)	(0.967)	(0.731)	(0.949)
GETS-DDD	3.449	3.947	4.420	3.514	4.457	-0.682	3.514	7.235	3.764	4.479	3.543	4.855
	(0.999)	(1.000)	(1.000)	(0.999)	(1.000)	(0.250)	(0.999)	(1.000)	(1.000)	(1.000)	(0.999)	(1.000)
GETS-IIS-DDD	4.828	3.451	3.620	3.175	4.241	-0.639	3.064	6.289	3.257	4.133	3.100	4.313
	(1.000)	(0.999)	(0.999)	(0.998)	(1.000)	(0.264)	(0.998)	(1.000)	(0.999)	(1.000)	(0.998)	(1.000)
GETS-SIS-DDD	4.379	3.887	3.565	3.178	4.173	-0.617	3.168	5.887	3.169	4.039	3.137	4.200
	(1.000)	(1.000)	(0.999)	(0.998)	(1.000)	(0.271)	(0.998)	(1.000)	(0.998)	(1.000)	(0.998)	(1.000)
Ridge, CV	-0.812	-1.048	-0.973	-1.115	0.110	**-2.175**	-1.263	-0.709	-0.836	1.464	-1.006	1.538
	(0.212)	(0.152)	(0.169)	(0.137)	(0.543)	**(0.019)**	(0.108)	(0.242)	(0.205)	(0.923)	(0.161)	(0.932)
Lasso, CV	-0.482	-0.576	0.121	-0.052	0.654	**-2.054**	0.170	0.108	0.263	1.649	-0.272	1.892
	(0.317)	(0.285)	(0.548)	(0.480)	(0.741)	**(0.025)**	(0.567)	(0.542)	(0.603)	(0.945)	(0.394)	(0.966)
ELNET, CV	-0.460	-0.543	0.168	0.003	0.671	**-2.035**	0.200	0.139	0.308	1.668	-0.232	1.924
	(0.324)	(0.296)	(0.566)	(0.501)	(0.746)	**(0.026)**	(0.578)	(0.555)	(0.620)	(0.947)	(0.409)	(0.968)
Ridge, AIC	-0.970	-1.446	-1.278	-1.473	-0.370	**-2.229**	-0.934	-1.464	-1.415	1.689	-1.343	1.312
	(0.170)	(0.080)	(0.106)	(0.076)	(0.357)	**(0.017)**	(0.179)	(0.077)	(0.084)	(0.949)	(0.095)	(0.900)
Lasso, AIC	1.183	1.047	1.019	1.016	1.097	0.388	1.049	1.106	1.018	1.151	0.998	1.141
	(0.877)	(0.848)	(0.841)	(0.841)	(0.859)	(0.649)	(0.848)	(0.861)	(0.841)	(0.870)	(0.837)	(0.868)
ELNET, AIC	1.284	1.100	1.059	1.063	1.163	0.316	1.101	1.180	1.062	1.223	1.036	1.208
	(0.895)	(0.860)	(0.851)	(0.851)	(0.873)	(0.623)	(0.860)	(0.876)	(0.851)	(0.884)	(0.845)	(0.881)
k-NN	0.076	0.249	0.787	0.671	1.294	-1.306	1.029	0.776	1.583	2.035	0.528	1.856
	(0.530)	(0.597)	(0.781)	(0.746)	(0.897)	(0.101)	(0.844)	(0.778)	(0.938)	(0.974)	(0.699)	(0.963)
wk-NN	-0.171	-0.073	0.492	0.371	0.997	-1.611	0.704	0.435	1.282	1.785	0.207	1.712
	(0.433)	(0.471)	(0.687)	(0.643)	(0.836)	(0.059)	(0.756)	(0.667)	(0.895)	(0.957)	(0.581)	(0.951)
RF	-0.834	-1.195	-1.581	-1.471	-0.199	**-2.326**	**-1.974**	-0.890	-1.392	1.417	-1.347	1.435
	(0.206)	(0.121)	(0.063)	(0.076)	(0.422)	**(0.014)**	**(0.029)**	(0.191)	(0.087)	(0.916)	(0.094)	(0.919)
FFNN	-1.081	-1.497	-1.021	-1.178	**-3.388**	**-2.172**	-1.053	-1.471	-1.133	0.670	-1.235	0.159
	(0.144)	(0.073)	(0.158)	(0.124)	**(0.001)**	**(0.019)**	(0.151)	(0.076)	(0.133)	(0.746)	(0.114)	(0.563)
RNN	-0.262	-0.257	0.885	0.669	2.975	**-1.864**	0.522	0.677	1.017	2.319	0.312	2.374
	(0.398)	(0.399)	(0.808)	(0.746)	(0.997)	**(0.036)**	(0.697)	(0.748)	(0.841)	(0.986)	(0.621)	(0.988)
SVR-LIN	-1.305	**-1.962**	**-2.006**	**-2.156**	**-3.081**	**-2.437**	**-2.380**	**-2.128**	**-2.332**	**-2.177**	**-2.033**	-1.330
	(0.101)	**(0.030)**	**(0.027)**	**(0.020)**	**(0.002)**	**(0.011)**	**(0.012)**	**(0.021)**	**(0.014)**	**(0.019)**	**(0.026)**	(0.097)
SVR-POLY	-1.235	**-1.905**	**-2.024**	**-2.050**	**-2.300**	**-2.423**	**-2.276**	**-2.050**	**-2.633**	**-2.086**	**-1.971**	-1.348
	(0.114)	**(0.034)**	**(0.026)**	**(0.025)**	**(0.015)**	**(0.011)**	**(0.015)**	**(0.025)**	**(0.007)**	**(0.023)**	**(0.029)**	(0.094)
SVR-RBF	-0.935	-1.485	**-2.314**	**-1.878**	-0.628	**-2.418**	**-3.012**	-1.229	**-2.261**	0.766	**-1.763**	0.449
	(0.179)	(0.074)	**(0.014)**	**(0.035)**	(0.268)	**(0.011)**	**(0.003)**	(0.115)	**(0.016)**	(0.775)	**(0.044)**	(0.672)
SVR-ANOVA	-	0.220	0.443	0.432	0.852	-1.160	0.628	0.823	0.511	1.139	0.325	1.036
	-	(0.586)	(0.669)	(0.666)	(0.799)	(0.128)	(0.732)	(0.791)	(0.693)	(0.868)	(0.626)	(0.845)
AR+SVR-POLY	-0.220	-	0.731	0.564	1.185	**-1.864**	0.742	0.952	0.597	1.751	0.469	1.779
	(0.414)	-	(0.764)	(0.712)	(0.877)	**(0.036)**	(0.768)	(0.825)	(0.722)	(0.955)	(0.678)	(0.957)
AR+SVR-RBF	-0.443	-0.731	-	-0.252	0.714	**-2.361**	0.226	0.015	0.163	1.869	-0.745	2.275
	(0.331)	(0.236)	-	(0.401)	(0.759)	**(0.013)**	(0.589)	(0.506)	(0.564)	(0.964)	(0.231)	(0.985)
AR+SVR-ANOVA	-0.432	-0.564	0.252	-	0.930	**-2.416**	0.309	0.119	0.249	1.916	-0.633	1.892
	(0.334)	(0.288)	(0.599)	-	(0.820)	**(0.011)**	(0.620)	(0.547)	(0.597)	(0.967)	(0.266)	(0.966)
AR+FFNN	-0.852	-1.185	-0.714	-0.930	-	**-2.164**	-0.654	-0.853	-0.606	1.686	-1.017	0.957
	(0.201)	(0.123)	(0.241)	(0.180)	-	**(0.020)**	(0.259)	(0.200)	(0.275)	(0.949)	(0.159)	(0.827)
AR+RNN	1.160	1.864	2.361	2.416	2.164	-	2.119	1.880	1.981	2.362	2.499	2.399
	(0.872)	(0.964)	(0.987)	(0.989)	(0.980)	-	(0.978)	(0.965)	(0.971)	(0.987)	(0.991)	(0.988)
Ave. BM	-0.628	-0.742	-0.226	-0.309	0.654	**-2.119**	-	-0.084	0.070	2.245	-0.546	3.086
	(0.268)	(0.232)	(0.411)	(0.380)	(0.741)	**(0.022)**	-	(0.467)	(0.528)	(0.984)	(0.295)	(0.998)
Ave. Linear	-0.823	-0.952	-0.015	-0.119	0.853	**-1.880**	0.084	-	0.107	1.798	-0.307	1.652
	(0.209)	(0.175)	(0.494)	(0.453)	(0.800)	**(0.035)**	(0.533)	-	(0.542)	(0.959)	(0.381)	(0.945)
Ave. Local	-0.511	-0.597	-0.163	-0.249	0.606	**-1.981**	-0.070	-0.107	-	2.122	-0.408	2.108
	(0.307)	(0.278)	(0.436)	(0.403)	(0.725)	**(0.029)**	(0.472)	(0.458)	-	(0.979)	(0.343)	(0.978)
Ave. Non-linear	-1.139	**-1.751**	**-1.869**	**-1.916**	-1.686	**-2.362**	**-2.245**	**-1.798**	**-2.122**	-	**-1.817**	-0.868
	(0.132)	**(0.045)**	**(0.036)**	**(0.033)**	(0.051)	**(0.013)**	**(0.016)**	**(0.041)**	**(0.021)**	-	**(0.040)**	(0.197)
Ave. AR+	-0.325	-0.469	0.745	0.633	1.017	**-2.499**	0.546	0.307	0.408	1.817	-	1.891
	(0.374)	(0.322)	(0.769)	(0.734)	(0.841)	**(0.009)**	(0.705)	(0.619)	(0.657)	(0.960)	-	(0.966)
Tot. Ave.	-1.036	**-1.779**	**-2.275**	**-1.892**	-0.957	**-2.399**	**-3.086**	-1.652	**-2.108**	0.868	**-1.891**	-
	(0.155)	**(0.043)**	**(0.015)**	**(0.034)**	(0.173)	**(0.012)**	**(0.002)**	(0.055)	**(0.022)**	(0.803)	**(0.034)**	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.28: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 4$. $N = 28$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.774	-0.419	-1.246	-1.170	-1.190	-1.337	-1.467	-1.476	-1.575	0.140	-0.070
	-	(0.223)	(0.339)	(0.112)	(0.126)	(0.122)	(0.096)	(0.077)	(0.076)	(0.063)	(0.555)	(0.472)
RW	0.774	-	1.022	0.286	-1.147	-1.172	-1.306	-1.583	-1.592	**-2.109**	0.938	0.832
	(0.777)	-	(0.842)	(0.612)	(0.131)	(0.126)	(0.101)	(0.063)	(0.062)	**(0.022)**	(0.822)	(0.794)
DDD	0.419	-1.022	-	-0.366	-1.161	-1.184	-1.323	-1.441	-1.452	-1.562	0.635	0.438
	(0.661)	(0.158)	-	(0.359)	(0.128)	(0.123)	(0.098)	(0.081)	(0.079)	(0.065)	(0.735)	(0.668)
VAR(4)	1.246	-0.286	0.366	-	-1.139	-1.160	-1.284	-1.474	-1.483	-1.611	1.049	0.887
	(0.888)	(0.388)	(0.641)	-	(0.132)	(0.128)	(0.105)	(0.076)	(0.075)	(0.059)	(0.848)	(0.808)
GETS	1.170	1.147	1.161	1.139	-	0.219	0.327	0.986	0.978	1.008	1.144	1.133
	(0.874)	(0.869)	(0.872)	(0.868)	-	(0.586)	(0.627)	(0.834)	(0.832)	(0.839)	(0.869)	(0.866)
GETS-IIS	1.190	1.172	1.184	1.160	-0.219	-	0.326	1.009	1.000	1.028	1.164	1.153
	(0.878)	(0.874)	(0.877)	(0.872)	(0.414)	-	(0.626)	(0.839)	(0.837)	(0.843)	(0.873)	(0.871)
GETS-SIS	1.337	1.306	1.323	1.284	-0.327	-0.326	-	1.096	1.089	1.137	1.289	1.280
	(0.904)	(0.899)	(0.902)	(0.895)	(0.373)	(0.374)	-	(0.859)	(0.857)	(0.867)	(0.896)	(0.894)
GETS-DDD	1.467	1.583	1.441	1.474	-0.986	-1.009	-1.096	-	-0.690	1.157	1.366	1.330
	(0.923)	(0.937)	(0.919)	(0.924)	(0.166)	(0.161)	(0.141)	-	(0.248)	(0.871)	(0.908)	(0.903)
GETS-IIS-DDD	1.476	1.592	1.452	1.483	-0.978	-1.000	-1.089	0.690	-	1.205	1.377	1.342
	(0.924)	(0.938)	(0.921)	(0.925)	(0.168)	(0.163)	(0.143)	(0.752)	-	(0.881)	(0.910)	(0.905)
GETS-SIS-DDD	1.575	2.109	1.562	1.611	-1.008	-1.028	-1.137	-1.157	-1.205	-	1.411	1.366
	(0.937)	(0.978)	(0.935)	(0.941)	(0.161)	(0.157)	(0.133)	(0.129)	(0.119)	-	(0.915)	(0.908)
Ridge, CV	-0.140	-0.938	-0.635	-1.049	-1.144	-1.164	-1.289	-1.366	-1.377	-1.411	-	-0.616
	(0.445)	(0.178)	(0.265)	(0.152)	(0.131)	(0.127)	(0.104)	(0.092)	(0.090)	(0.085)	-	(0.272)
Lasso, CV	0.070	-0.832	-0.438	-0.887	-1.133	-1.153	-1.280	-1.330	-1.342	-1.366	0.616	-
	(0.528)	(0.206)	(0.332)	(0.192)	(0.134)	(0.129)	(0.106)	(0.097)	(0.095)	(0.092)	(0.728)	-
ELNET, CV	0.120	-0.839	-0.428	-0.901	-1.138	-1.158	-1.288	-1.351	-1.362	-1.397	0.615	0.199
	(0.547)	(0.204)	(0.336)	(0.188)	(0.132)	(0.128)	(0.104)	(0.094)	(0.092)	(0.087)	(0.728)	(0.578)
Ridge, AIC	1.161	1.878	1.140	1.038	-1.136	-1.161	-1.282	-1.665	-1.687	-1.591	1.096	1.030
	(0.872)	(0.964)	(0.868)	(0.846)	(0.133)	(0.128)	(0.105)	(0.054)	(0.052)	(0.062)	(0.859)	(0.844)
Lasso, AIC	1.865	1.664	1.765	1.733	-0.119	-0.117	-0.006	1.199	1.192	1.510	1.773	1.778
	(0.963)	(0.946)	(0.956)	(0.953)	(0.453)	(0.454)	(0.498)	(0.880)	(0.878)	(0.929)	(0.956)	(0.957)
ELNET, AIC	1.878	1.753	1.813	1.789	0.011	0.016	0.225	1.568	1.572	1.764	1.795	1.796
	(0.964)	(0.955)	(0.960)	(0.958)	(0.504)	(0.506)	(0.588)	(0.936)	(0.936)	(0.955)	(0.958)	(0.958)
k-NN	0.655	-0.074	0.569	0.251	-1.001	-1.016	-1.090	-0.952	-0.959	-0.844	0.718	0.634
	(0.741)	(0.471)	(0.713)	(0.598)	(0.163)	(0.159)	(0.143)	(0.175)	(0.173)	(0.203)	(0.760)	(0.734)
wk-NN	0.329	**-2.014**	-0.040	-0.404	-1.097	-1.115	-1.221	-1.215	-1.220	-1.202	0.427	0.298
	(0.628)	**(0.027)**	(0.484)	(0.345)	(0.141)	(0.137)	(0.116)	(0.117)	(0.116)	(0.120)	(0.664)	(0.616)
RF	-1.071	-1.330	-1.510	**-1.728**	-1.184	-1.204	-1.336	-1.467	-1.475	-1.553	**-1.779**	**-2.177**
	(0.147)	(0.097)	(0.071)	**(0.048)**	(0.123)	(0.119)	(0.096)	(0.077)	(0.076)	(0.066)	**(0.043)**	**(0.019)**
FFNN	1.741	0.058	2.810	0.707	-1.018	-1.034	-1.128	-1.035	-1.049	-0.957	2.855	2.255
	(0.953)	(0.523)	(0.995)	(0.757)	(0.159)	(0.155)	(0.135)	(0.155)	(0.152)	(0.174)	(0.996)	(0.984)
RNN	2.473	1.455	2.507	1.384	-0.877	-0.890	-0.961	-0.679	-0.698	-0.504	4.894	4.100
	(0.990)	(0.921)	(0.991)	(0.911)	(0.194)	(0.191)	(0.173)	(0.251)	(0.246)	(0.309)	(1.000)	(1.000)
SVR-LIN	-0.469	-0.769	-0.486	-1.573	-1.183	-1.204	-1.353	-1.506	-1.513	-1.634	-0.081	-0.283
	(0.321)	(0.224)	(0.316)	(0.064)	(0.124)	(0.120)	(0.094)	(0.072)	(0.071)	(0.057)	(0.468)	(0.390)
SVR-POLY	-1.403	**-2.840**	**-1.950**	-1.544	-1.195	-1.214	-1.347	-1.460	-1.465	-1.535	**-1.772**	**-1.998**
	(0.086)	**(0.004)**	**(0.031)**	(0.067)	(0.121)	(0.118)	(0.095)	(0.078)	(0.077)	(0.068)	**(0.044)**	**(0.028)**
SVR-RBF	-0.767	-1.372	**-3.099**	-1.652	-1.193	-1.214	-1.338	-1.502	-1.509	-1.584	-1.411	-1.412
	(0.225)	(0.091)	**(0.002)**	(0.055)	(0.122)	(0.118)	(0.096)	(0.072)	(0.071)	(0.062)	(0.085)	(0.085)
SVR-ANOVA	0.534	-0.667	-0.199	-0.798	-1.130	-1.150	-1.279	-1.361	-1.373	-1.415	1.027	0.602
	(0.701)	(0.255)	(0.422)	(0.216)	(0.134)	(0.130)	(0.106)	(0.092)	(0.090)	(0.084)	(0.843)	(0.724)
AR+SVR-POLY	1.164	-0.129	1.044	0.193	-1.031	-1.047	-1.163	-1.049	-1.063	-1.002	1.054	0.962
	(0.873)	(0.449)	(0.847)	(0.576)	(0.156)	(0.152)	(0.127)	(0.152)	(0.149)	(0.163)	(0.849)	(0.828)
AR+SVR-RBF	1.295	-0.164	0.390	0.189	-1.056	-1.073	-1.179	-1.127	-1.140	-1.093	1.558	1.209
	(0.897)	(0.436)	(0.650)	(0.574)	(0.150)	(0.146)	(0.124)	(0.135)	(0.132)	(0.142)	(0.935)	(0.881)
AR+SVR-ANOVA	0.913	-0.421	0.653	0.146	-1.014	-1.029	-1.137	-1.018	-1.032	-0.964	0.967	0.878
	(0.815)	(0.338)	(0.740)	(0.558)	(0.160)	(0.156)	(0.133)	(0.159)	(0.156)	(0.172)	(0.829)	(0.806)
AR+FFNN	1.141	0.166	0.895	0.422	-0.947	-0.961	-1.042	-0.832	-0.845	-0.720	1.510	1.301
	(0.868)	(0.565)	(0.811)	(0.662)	(0.176)	(0.173)	(0.153)	(0.206)	(0.203)	(0.239)	(0.929)	(0.898)
AR+RNN	2.357	1.504	2.275	1.568	-0.832	-0.845	-0.895	-0.513	-0.529	-0.283	3.664	3.467
	(0.987)	(0.928)	(0.984)	(0.936)	(0.206)	(0.203)	(0.189)	(0.306)	(0.300)	(0.390)	(0.999)	(0.999)
Ave. BM	-0.474	-1.615	-1.636	-1.612	-1.189	-1.212	-1.335	-1.506	-1.514	-1.598	-0.684	-0.824
	(0.320)	(0.059)	(0.057)	(0.059)	(0.122)	(0.118)	(0.097)	(0.072)	(0.071)	(0.061)	(0.250)	(0.209)
Ave. Linear	0.977	0.935	0.953	0.874	-1.216	-1.248	-1.381	**-2.478**	**-2.490**	-0.794	0.935	0.894
	(0.831)	(0.821)	(0.825)	(0.805)	(0.117)	(0.111)	(0.089)	**(0.010)**	**(0.010)**	(0.217)	(0.821)	(0.810)
Ave. Local	-0.107	-0.824	-0.912	-0.877	-1.128	-1.146	-1.259	-1.308	-1.313	-1.329	-0.017	-0.169
	(0.458)	(0.208)	(0.185)	(0.194)	(0.135)	(0.131)	(0.109)	(0.101)	(0.100)	(0.098)	(0.493)	(0.433)
Ave. Non-linear	-0.696	-1.151	**-2.246**	-1.434	-1.177	-1.198	-1.320	-1.468	-1.476	-1.541	**-1.757**	-1.604
	(0.246)	(0.130)	**(0.017)**	(0.082)	(0.125)	(0.121)	(0.099)	(0.077)	(0.076)	(0.068)	**(0.045)**	(0.060)
Ave. AR+	0.611	**-2.559**	0.294	-0.173	-1.053	-1.069	-1.174	-1.117	-1.128	-1.087	0.878	0.687
	(0.727)	**(0.008)**	(0.614)	(0.432)	(0.151)	(0.147)	(0.125)	(0.137)	(0.135)	(0.143)	(0.806)	(0.751)
Tot. Ave.	0.656	-0.240	0.650	0.034	-1.199	-1.222	-1.357	-1.673	-1.680	**-1.837**	0.639	0.530
	(0.741)	(0.406)	(0.739)	(0.513)	(0.121)	(0.116)	(0.093)	(0.053)	(0.052)	**(0.039)**	(0.736)	(0.700)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.29: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 4$. $N = 28$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	-0.120	-1.161	**-1.865**	**-1.878**	-0.655	-0.329	1.071	**-1.741**	**-2.473**	0.469	1.403	0.767
	(0.453)	(0.128)	**(0.037)**	**(0.036)**	(0.259)	(0.372)	(0.853)	**(0.047)**	**(0.010)**	(0.679)	(0.914)	(0.775)
RW	0.839	**-1.878**	-1.664	**-1.753**	0.074	2.014	1.330	-0.058	-1.455	0.769	2.840	1.372
	(0.796)	**(0.036)**	(0.054)	**(0.045)**	(0.529)	(0.973)	(0.903)	(0.477)	(0.079)	(0.776)	(0.996)	(0.909)
DDD	0.428	-1.140	**-1.765**	**-1.813**	-0.569	0.040	1.510	**-2.810**	**-2.507**	0.486	1.950	3.099
	(0.664)	(0.132)	**(0.044)**	**(0.040)**	(0.287)	(0.516)	(0.929)	**(0.005)**	**(0.009)**	(0.684)	(0.969)	(0.998)
VAR(4)	0.901	-1.038	**-1.733**	**-1.789**	-0.251	0.404	1.728	-0.707	-1.384	1.573	1.544	1.652
	(0.812)	(0.154)	**(0.047)**	**(0.042)**	(0.402)	(0.655)	(0.952)	(0.243)	(0.089)	(0.936)	(0.933)	(0.945)
GETS	1.138	1.136	0.119	-0.011	1.001	1.097	1.184	1.018	0.877	1.183	1.195	1.193
	(0.868)	(0.867)	(0.547)	(0.496)	(0.837)	(0.859)	(0.877)	(0.841)	(0.806)	(0.876)	(0.879)	(0.878)
GETS-IIS	1.158	1.161	0.117	-0.016	1.016	1.115	1.204	1.034	0.890	1.204	1.214	1.214
	(0.872)	(0.872)	(0.546)	(0.494)	(0.841)	(0.863)	(0.881)	(0.845)	(0.809)	(0.880)	(0.882)	(0.882)
GETS-SIS	1.288	1.282	0.006	-0.225	1.090	1.221	1.336	1.128	0.961	1.353	1.347	1.338
	(0.896)	(0.895)	(0.502)	(0.412)	(0.857)	(0.884)	(0.904)	(0.865)	(0.827)	(0.906)	(0.905)	(0.904)
GETS-DDD	1.351	1.665	-1.199	-1.568	0.952	1.215	1.467	1.035	0.679	1.506	1.460	1.502
	(0.906)	(0.946)	(0.120)	(0.064)	(0.825)	(0.883)	(0.923)	(0.845)	(0.749)	(0.928)	(0.922)	(0.928)
GETS-IIS-DDD	1.362	1.687	-1.192	-1.572	0.959	1.220	1.475	1.049	0.698	1.513	1.465	1.509
	(0.908)	(0.948)	(0.122)	(0.064)	(0.827)	(0.884)	(0.924)	(0.848)	(0.754)	(0.929)	(0.923)	(0.929)
GETS-SIS-DDD	1.397	1.591	-1.510	**-1.764**	0.844	1.202	1.553	0.957	0.504	1.634	1.535	1.584
	(0.913)	(0.938)	(0.071)	**(0.045)**	(0.797)	(0.880)	(0.934)	(0.826)	(0.691)	(0.943)	(0.932)	(0.938)
Ridge, CV	-0.615	-1.096	**-1.773**	**-1.795**	-0.718	-0.427	1.779	**-2.855**	**-4.894**	0.081	1.772	1.411
	(0.272)	(0.141)	**(0.044)**	**(0.042)**	(0.240)	(0.336)	(0.957)	**(0.004)**	**(0.000)**	(0.532)	(0.956)	(0.915)
Lasso, CV	-0.199	-1.030	**-1.778**	**-1.796**	-0.634	-0.298	2.177	**-2.255**	**-4.100**	0.283	1.998	1.412
	(0.422)	(0.156)	**(0.043)**	**(0.042)**	(0.266)	(0.384)	(0.981)	**(0.016)**	**(0.000)**	(0.610)	(0.972)	(0.915)
ELNET, CV	-	-1.049	**-1.791**	**-1.808**	-0.615	-0.269	1.838	**-2.465**	**-4.259**	0.363	1.904	1.243
	-	(0.152)	**(0.042)**	**(0.041)**	(0.272)	(0.395)	(0.961)	**(0.010)**	**(0.000)**	(0.640)	(0.966)	(0.888)
Ridge, AIC	1.049	-	-1.586	**-1.771**	0.428	0.805	1.257	0.511	0.020	1.223	1.275	1.332
	(0.848)	-	(0.062)	**(0.044)**	(0.664)	(0.786)	(0.890)	(0.693)	(0.508)	(0.884)	(0.893)	(0.903)
Lasso, AIC	1.791	1.586	-	-0.750	1.397	1.605	1.829	1.601	1.409	1.887	1.850	1.784
	(0.958)	(0.938)	-	(0.230)	(0.913)	(0.940)	(0.961)	(0.939)	(0.915)	(0.965)	(0.962)	(0.957)
ELNET, AIC	1.808	1.771	0.750	-	1.452	1.646	1.842	1.637	1.430	1.899	1.842	1.818
	(0.959)	(0.956)	(0.770)	-	(0.921)	(0.944)	(0.962)	(0.943)	(0.918)	(0.966)	(0.962)	(0.960)
k-NN	0.615	-0.428	-1.397	-1.452	-	1.095	1.297	-0.103	-0.686	0.734	1.622	1.189
	(0.728)	(0.336)	(0.087)	(0.079)	-	(0.859)	(0.897)	(0.459)	(0.249)	(0.765)	(0.942)	(0.878)
wk-NN	0.269	-0.805	-1.605	-1.646	-1.095	-	1.611	-0.811	-1.658	0.474	2.024	1.194
	(0.605)	(0.214)	(0.060)	(0.056)	(0.141)	-	(0.941)	(0.212)	(0.054)	(0.680)	(0.973)	(0.879)
RF	**-1.838**	-1.257	**-1.829**	**-1.842**	-1.297	-1.611	-	**-2.629**	**-4.130**	-0.826	1.190	-0.171
	(0.039)	(0.110)	**(0.039)**	**(0.038)**	(0.103)	(0.059)	-	**(0.007)**	**(0.000)**	(0.208)	(0.878)	(0.433)
FFNN	2.465	-0.511	-1.601	-1.637	0.103	0.811	2.629	-	**-2.000**	1.781	2.776	2.980
	(0.990)	(0.307)	(0.061)	(0.057)	(0.541)	(0.788)	(0.993)	-	**(0.028)**	(0.957)	(0.995)	(0.997)
RNN	4.259	-0.020	-1.409	-1.430	0.686	1.658	4.130	2.000	-	2.591	6.012	3.309
	(1.000)	(0.492)	(0.085)	(0.082)	(0.751)	(0.946)	(1.000)	(0.972)	-	(0.992)	(1.000)	(0.999)
SVR-LIN	-0.363	-1.223	**-1.887**	**-1.899**	-0.734	-0.474	0.826	**-1.781**	**-2.591**	-	1.200	0.588
	(0.360)	(0.116)	**(0.035)**	**(0.034)**	(0.235)	(0.320)	(0.792)	**(0.043)**	**(0.008)**	-	(0.880)	(0.719)
SVR-POLY	**-1.904**	-1.275	**-1.850**	**-1.842**	-1.622	**-2.024**	-1.190	**-2.776**	**-6.012**	-1.200	-	-0.823
	(0.034)	(0.107)	**(0.038)**	**(0.038)**	(0.058)	**(0.027)**	(0.122)	**(0.005)**	**(0.000)**	(0.120)	-	(0.209)
SVR-RBF	-1.243	-1.332	**-1.784**	**-1.818**	-1.189	-1.194	0.171	**-2.980**	**-3.309**	-0.588	0.823	-
	(0.112)	(0.097)	**(0.043)**	**(0.040)**	(0.122)	(0.121)	(0.567)	**(0.003)**	**(0.001)**	(0.281)	(0.791)	-
SVR-ANOVA	0.261	-1.038	**-1.827**	**-1.834**	-0.527	-0.147	1.736	**-2.882**	**-4.429**	0.773	1.786	1.295
	(0.602)	(0.154)	**(0.039)**	**(0.039)**	(0.301)	(0.442)	(0.953)	**(0.004)**	**(0.000)**	(0.777)	(0.957)	(0.897)
AR+SVR-POLY	0.975	-0.563	**-1.754**	**-1.740**	-0.096	0.495	1.798	-0.361	-1.644	1.351	2.682	1.391
	(0.831)	(0.289)	**(0.045)**	**(0.047)**	(0.462)	(0.688)	(0.958)	(0.360)	(0.056)	(0.906)	(0.994)	(0.912)
AR+SVR-RBF	1.201	-0.668	-1.665	-1.692	-0.150	0.545	2.547	-0.620	**-1.889**	1.508	2.904	2.349
	(0.880)	(0.255)	(0.054)	(0.051)	(0.441)	(0.705)	(0.992)	(0.270)	**(0.035)**	(0.928)	(0.996)	(0.987)
AR+SVR-ANOVA	0.875	-0.540	**-1.728**	**-1.710**	-0.109	0.447	1.665	-0.382	**-2.103**	1.043	2.485	1.282
	(0.805)	(0.297)	**(0.048)**	**(0.049)**	(0.457)	(0.671)	(0.946)	(0.353)	**(0.022)**	(0.847)	(0.990)	(0.895)
AR+FFNN	1.314	-0.351	-1.488	-1.499	0.127	0.768	2.065	0.041	-0.781	1.210	5.017	1.787
	(0.900)	(0.364)	(0.074)	(0.073)	(0.550)	(0.775)	(0.976)	(0.516)	(0.221)	(0.882)	(1.000)	(0.957)
AR+RNN	3.095	0.215	-1.198	-1.262	1.121	2.756	4.576	1.772	0.465	2.453	5.157	4.859
	(0.998)	(0.584)	(0.121)	(0.109)	(0.864)	(0.995)	(1.000)	(0.956)	(0.677)	(0.990)	(1.000)	(1.000)
Ave. BM	-0.716	-1.308	**-1.761**	**-1.807**	-1.160	-1.007	0.902	**-2.564**	**-2.748**	-0.315	1.019	0.617
	(0.240)	(0.101)	**(0.045)**	**(0.041)**	(0.128)	(0.161)	(0.812)	**(0.008)**	**(0.005)**	(0.378)	(0.841)	(0.729)
Ave. Linear	0.903	0.549	-1.472	**-1.747**	0.497	0.769	1.066	0.529	0.179	1.021	1.098	1.106
	(0.813)	(0.706)	(0.076)	**(0.046)**	(0.689)	(0.776)	(0.852)	(0.699)	(0.570)	(0.842)	(0.859)	(0.861)
Ave. Local	-0.184	-0.968	-1.676	**-1.708**	-1.327	**-3.615**	1.237	-1.269	**-2.271**	0.042	1.730	0.850
	(0.428)	(0.171)	(0.053)	**(0.050)**	(0.098)	**(0.001)**	(0.887)	(0.108)	**(0.016)**	(0.517)	(0.952)	(0.799)
Ave. Non-linear	-1.387	-1.275	**-1.780**	**-1.807**	-1.047	-1.017	0.467	**-4.092**	**-3.977**	-0.502	1.076	0.467
	(0.088)	(0.107)	**(0.043)**	**(0.041)**	(0.152)	(0.159)	(0.678)	**(0.000)**	**(0.000)**	(0.310)	(0.854)	(0.678)
Ave. AR+	0.645	-0.710	-1.690	-1.696	-0.355	0.201	2.003	-1.036	**-2.557**	0.770	3.618	1.516
	(0.738)	(0.242)	(0.051)	(0.051)	(0.363)	(0.579)	(0.972)	(0.155)	**(0.008)**	(0.776)	(0.999)	(0.929)
Tot. Ave.	0.536	-1.539	**-1.755**	**-1.852**	-0.174	0.263	1.006	-0.436	-0.887	0.776	1.091	1.105
	(0.702)	(0.068)	**(0.045)**	**(0.038)**	(0.431)	(0.603)	(0.838)	(0.333)	(0.192)	(0.778)	(0.858)	(0.861)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.30: Modified Diebold-Marino (DM) test for equal forecast accuracy. GDP-growth. Multivariate. $h = 4$. $N = 28$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-0.534	-1.164	-1.295	-0.913	-1.141	**-2.357**	0.474	-0.977	0.107	0.696	-0.611	-0.656
	(0.299)	(0.127)	(0.103)	(0.185)	(0.132)	**(0.013)**	(0.680)	(0.169)	(0.542)	(0.754)	(0.273)	(0.259)
RW	0.667	0.129	0.164	0.421	-0.166	-1.504	1.615	-0.935	0.824	1.151	2.559	0.240
	(0.745)	(0.551)	(0.564)	(0.662)	(0.435)	(0.072)	(0.941)	(0.179)	(0.792)	(0.870)	(0.992)	(0.594)
DDD	0.199	-1.044	-0.390	-0.653	-0.895	**-2.275**	1.636	-0.953	0.912	2.246	-0.294	-0.650
	(0.578)	(0.153)	(0.350)	(0.260)	(0.189)	**(0.016)**	(0.943)	(0.175)	(0.815)	(0.983)	(0.386)	(0.261)
VAR(4)	0.798	-0.193	-0.189	-0.146	-0.422	-1.568	1.612	-0.874	0.877	1.434	0.173	-0.034
	(0.784)	(0.424)	(0.426)	(0.442)	(0.338)	(0.064)	(0.941)	(0.195)	(0.806)	(0.918)	(0.568)	(0.487)
GETS	1.130	1.031	1.056	1.014	0.947	0.832	1.189	1.216	1.128	1.177	1.053	1.199
	(0.866)	(0.844)	(0.850)	(0.840)	(0.824)	(0.794)	(0.878)	(0.883)	(0.865)	(0.875)	(0.849)	(0.879)
GETS-IIS	1.150	1.047	1.073	1.029	0.961	0.845	1.212	1.248	1.146	1.198	1.069	1.222
	(0.870)	(0.848)	(0.854)	(0.844)	(0.827)	(0.797)	(0.882)	(0.889)	(0.869)	(0.879)	(0.853)	(0.884)
GETS-SIS	1.279	1.163	1.179	1.137	1.042	0.895	1.335	1.381	1.259	1.320	1.174	1.357
	(0.894)	(0.873)	(0.876)	(0.867)	(0.847)	(0.811)	(0.903)	(0.911)	(0.891)	(0.901)	(0.875)	(0.907)
GETS-DDD	1.361	1.049	1.127	1.018	0.832	0.513	1.506	2.478	1.308	1.468	1.117	1.673
	(0.908)	(0.848)	(0.865)	(0.841)	(0.794)	(0.694)	(0.928)	(0.990)	(0.899)	(0.923)	(0.863)	(0.947)
GETS-IIS-DDD	1.373	1.063	1.140	1.032	0.845	0.529	1.514	2.490	1.313	1.476	1.128	1.680
	(0.910)	(0.851)	(0.868)	(0.844)	(0.797)	(0.700)	(0.929)	(0.990)	(0.900)	(0.924)	(0.865)	(0.948)
GETS-SIS-DDD	1.415	1.002	1.093	0.964	0.720	0.283	1.598	0.794	1.329	1.541	1.087	1.837
	(0.916)	(0.837)	(0.858)	(0.828)	(0.761)	(0.610)	(0.939)	(0.783)	(0.902)	(0.932)	(0.857)	(0.961)
Ridge, CV	-1.027	-1.054	-1.558	-0.967	-1.510	**-3.664**	0.684	-0.935	0.017	1.757	-0.878	-0.639
	(0.157)	(0.151)	(0.065)	(0.171)	(0.071)	**(0.001)**	(0.750)	(0.179)	(0.507)	(0.955)	(0.194)	(0.264)
Lasso, CV	-0.602	-0.962	-1.209	-0.878	-1.301	**-3.467**	0.824	-0.894	0.169	1.604	-0.687	-0.530
	(0.276)	(0.172)	(0.119)	(0.194)	(0.102)	**(0.001)**	(0.791)	(0.190)	(0.567)	(0.940)	(0.249)	(0.300)
ELNET, CV	-0.261	-0.975	-1.201	-0.875	-1.314	**-3.095**	0.716	-0.903	0.184	1.387	-0.645	-0.536
	(0.398)	(0.169)	(0.120)	(0.195)	(0.100)	**(0.002)**	(0.760)	(0.187)	(0.572)	(0.912)	(0.262)	(0.298)
Ridge, AIC	1.038	0.563	0.668	0.540	0.351	-0.215	1.308	-0.549	0.968	1.275	0.710	1.539
	(0.846)	(0.711)	(0.745)	(0.703)	(0.636)	(0.416)	(0.899)	(0.294)	(0.829)	(0.893)	(0.758)	(0.932)
Lasso, AIC	1.827	1.754	1.665	1.728	1.488	1.198	1.761	1.472	1.676	1.780	1.690	1.755
	(0.961)	(0.955)	(0.946)	(0.952)	(0.926)	(0.879)	(0.955)	(0.924)	(0.947)	(0.957)	(0.949)	(0.955)
ELNET, AIC	1.834	1.740	1.692	1.710	1.499	1.262	1.807	1.747	1.708	1.807	1.696	1.852
	(0.961)	(0.953)	(0.949)	(0.951)	(0.927)	(0.891)	(0.959)	(0.954)	(0.950)	(0.959)	(0.949)	(0.962)
k-NN	0.527	0.096	0.150	0.109	-0.127	-1.121	1.160	-0.497	1.327	1.047	0.355	0.174
	(0.699)	(0.538)	(0.559)	(0.543)	(0.450)	(0.136)	(0.872)	(0.311)	(0.902)	(0.848)	(0.637)	(0.569)
wk-NN	0.147	-0.495	-0.545	-0.447	-0.768	**-2.756**	1.007	-0.769	3.615	1.017	-0.201	-0.263
	(0.558)	(0.312)	(0.295)	(0.329)	(0.225)	**(0.005)**	(0.839)	(0.224)	(0.999)	(0.841)	(0.421)	(0.397)
RF	**-1.736**	**-1.798**	**-2.547**	-1.665	**-2.065**	**-4.576**	-0.902	-1.066	-1.237	-0.467	**-2.003**	-1.006
	(0.047)	**(0.042)**	**(0.008)**	(0.054)	**(0.024)**	**(0.000)**	(0.188)	(0.148)	(0.113)	(0.322)	**(0.028)**	(0.162)
FFNN	2.882	0.361	0.620	0.382	-0.041	**-1.772**	2.564	-0.529	1.269	4.092	1.036	0.436
	(0.996)	(0.640)	(0.730)	(0.647)	(0.484)	**(0.044)**	(0.992)	(0.301)	(0.892)	(1.000)	(0.845)	(0.667)
RNN	4.429	1.644	1.889	2.103	0.781	-0.465	2.748	-0.179	2.271	3.977	2.557	0.887
	(1.000)	(0.944)	(0.965)	(0.978)	(0.779)	(0.323)	(0.995)	(0.430)	(0.984)	(1.000)	(0.992)	(0.808)
SVR-LIN	-0.773	-1.351	-1.508	-1.043	-1.210	**-2.453**	0.315	-1.021	-0.042	0.502	-0.770	-0.776
	(0.223)	(0.094)	(0.072)	(0.153)	(0.118)	**(0.010)**	(0.622)	(0.158)	(0.483)	(0.690)	(0.224)	(0.222)
SVR-POLY	**-1.786**	**-2.682**	**-2.904**	**-2.485**	**-5.017**	**-5.157**	-1.019	-1.098	**-1.730**	-1.076	**-3.618**	-1.091
	(0.043)	**(0.006)**	**(0.004)**	**(0.010)**	**(0.000)**	**(0.000)**	(0.159)	(0.141)	**(0.048)**	(0.146)	**(0.001)**	(0.142)
SVR-RBF	-1.295	-1.391	**-2.349**	-1.282	**-1.787**	**-4.859**	-0.617	-1.106	-0.850	-0.467	-1.516	-1.105
	(0.103)	(0.088)	**(0.013)**	(0.105)	**(0.043)**	**(0.000)**	(0.271)	(0.139)	(0.201)	(0.322)	(0.071)	(0.139)
SVR-ANOVA	-	-0.906	-1.123	-0.778	-1.166	**-2.834**	0.884	-0.883	0.303	1.413	-0.478	-0.458
	-	(0.187)	(0.136)	(0.222)	(0.127)	**(0.004)**	(0.808)	(0.193)	(0.618)	(0.915)	(0.318)	(0.325)
AR+SVR-POLY	0.906	-	0.110	0.116	-0.412	-1.490	1.226	-0.577	0.895	1.377	0.817	0.110
	(0.813)	-	(0.543)	(0.546)	(0.342)	(0.074)	(0.885)	(0.284)	(0.811)	(0.910)	(0.789)	(0.543)
AR+SVR-RBF	1.123	-0.110	-	-0.056	-0.508	**-1.893**	2.457	-0.647	1.099	2.284	0.840	0.092
	(0.864)	(0.457)	-	(0.478)	(0.308)	**(0.035)**	(0.990)	(0.262)	(0.859)	(0.985)	(0.796)	(0.536)
AR+SVR-ANOVA	0.778	-0.116	0.056	-	-0.494	-1.489	1.100	-0.557	0.830	1.272	0.722	0.086
	(0.778)	(0.454)	(0.522)	-	(0.313)	(0.074)	(0.860)	(0.291)	(0.793)	(0.893)	(0.762)	(0.534)
AR+FFNN	1.166	0.412	0.508	0.494	-	-1.438	1.443	-0.411	1.178	2.024	1.183	0.289
	(0.873)	(0.658)	(0.692)	(0.687)	-	(0.081)	(0.920)	(0.342)	(0.875)	(0.974)	(0.877)	(0.613)
AR+RNN	2.834	1.490	1.893	1.489	1.438	-	3.717	-0.012	3.269	5.160	2.505	1.274
	(0.996)	(0.926)	(0.965)	(0.926)	(0.919)	-	(1.000)	(0.495)	(0.999)	(1.000)	(0.991)	(0.893)
Ave. BM	-0.884	-1.226	**-2.457**	-1.100	-1.443	**-3.717**	-	-1.088	-0.558	0.411	-1.176	-1.060
	(0.192)	(0.115)	**(0.010)**	(0.140)	(0.080)	**(0.000)**	-	(0.143)	(0.291)	(0.658)	(0.125)	(0.149)
Ave. Linear	0.883	0.577	0.647	0.557	0.411	0.012	1.088	-	0.880	1.057	0.677	1.097
	(0.807)	(0.716)	(0.738)	(0.709)	(0.658)	(0.505)	(0.857)	-	(0.807)	(0.850)	(0.748)	(0.859)
Ave. Local	-0.303	-0.895	-1.099	-0.830	-1.178	**-3.269**	0.558	-0.880	-	0.628	-0.711	-0.537
	(0.382)	(0.189)	(0.141)	(0.207)	(0.125)	**(0.001)**	(0.709)	(0.193)	-	(0.732)	(0.242)	(0.298)
Ave. Non-linear	-1.413	-1.377	**-2.284**	-1.272	**-2.024**	**-5.160**	-0.411	-1.057	-0.628	-	-1.536	-0.982
	(0.085)	(0.090)	**(0.015)**	(0.107)	**(0.026)**	**(0.000)**	(0.342)	(0.150)	(0.268)	-	(0.068)	(0.167)
Ave. AR+	0.478	-0.817	-0.840	-0.722	-1.183	**-2.505**	1.176	-0.677	0.711	1.536	-	-0.125
	(0.682)	(0.211)	(0.204)	(0.238)	(0.123)	**(0.009)**	(0.875)	(0.252)	(0.758)	(0.932)	-	(0.451)
Tot. Ave.	0.458	-0.110	-0.092	-0.086	-0.289	-1.274	1.060	-1.097	0.537	0.982	0.125	-
	(0.675)	(0.457)	(0.464)	(0.466)	(0.387)	(0.107)	(0.851)	(0.141)	(0.702)	(0.833)	(0.549)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.31: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 1$. $N = 31$.

	AR(1)	RW	DDD	AR(p)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.781	**-2.501**	0.578	0.536	0.086	-0.479	**-1.790**	-1.697	-1.484	0.200	0.115
	-	(0.221)	**(0.009)**	(0.716)	(0.702)	(0.534)	(0.318)	**(0.042)**	(0.050)	(0.074)	(0.579)	(0.545)
RW	0.781	-	**-2.729**	0.999	1.060	0.596	-0.033	-1.376	-1.298	-1.000	0.738	0.692
	(0.779)	-	**(0.005)**	(0.837)	(0.851)	(0.722)	(0.487)	(0.089)	(0.102)	(0.163)	(0.767)	(0.753)
DDD	2.501	2.729	-	2.514	2.507	2.233	1.655	1.452	0.871	1.410	2.387	2.380
	(0.991)	(0.995)	-	(0.991)	(0.991)	(0.983)	(0.946)	(0.922)	(0.805)	(0.916)	(0.988)	(0.988)
AR(p)	-0.578	-0.999	**-2.514**	-	0.163	-0.480	-1.164	**-2.244**	**-2.291**	**-2.260**	-0.725	-0.705
	(0.284)	(0.163)	**(0.009)**	-	(0.564)	(0.317)	(0.127)	**(0.016)**	**(0.015)**	**(0.016)**	(0.237)	(0.243)
GETS	-0.536	-1.060	**-2.507**	-0.163	-	-0.734	-1.470	**-2.159**	**-2.210**	**-2.242**	-0.796	-0.687
	(0.298)	(0.149)	**(0.009)**	(0.436)	-	(0.234)	(0.076)	**(0.019)**	**(0.017)**	**(0.016)**	(0.216)	(0.249)
GETS-IIS	-0.086	-0.596	**-2.233**	0.480	0.734	-	-1.086	**-1.867**	**-2.119**	**-1.875**	0.037	-0.035
	(0.466)	(0.278)	**(0.017)**	(0.683)	(0.766)	-	(0.143)	**(0.036)**	**(0.021)**	**(0.035)**	(0.515)	(0.486)
GETS-SIS	0.479	0.033	-1.655	1.164	1.470	1.086	-	-1.092	-1.377	-1.069	0.742	0.610
	(0.682)	(0.513)	(0.054)	(0.873)	(0.924)	(0.857)	-	(0.142)	(0.089)	(0.147)	(0.768)	(0.727)
GETS-DDD	1.790	1.376	-1.452	2.244	2.159	1.867	1.092	-	-0.531	0.749	1.723	1.658
	(0.958)	(0.911)	(0.078)	(0.984)	(0.981)	(0.964)	(0.858)	-	(0.300)	(0.770)	(0.952)	(0.946)
GETS-IIS-DDD	1.697	1.298	-0.871	2.291	2.210	2.119	1.377	0.531	-	1.101	1.770	1.686
	(0.950)	(0.898)	(0.195)	(0.985)	(0.983)	(0.979)	(0.911)	(0.700)	-	(0.860)	(0.957)	(0.949)
GETS-SIS-DDD	1.484	1.000	-1.410	2.260	2.242	1.875	1.069	-0.749	-1.101	-	1.574	1.453
	(0.926)	(0.837)	(0.084)	(0.984)	(0.984)	(0.965)	(0.853)	(0.230)	(0.140)	-	(0.937)	(0.922)
Ridge, CV	-0.200	-0.738	**-2.387**	0.725	0.796	-0.037	-0.742	**-1.723**	**-1.770**	-1.574	-	-0.214
	(0.421)	(0.233)	**(0.012)**	(0.763)	(0.784)	(0.485)	(0.232)	**(0.048)**	**(0.043)**	(0.063)	-	(0.416)
Lasso, CV	-0.115	-0.692	**-2.380**	0.705	0.687	0.035	-0.610	-1.658	-1.686	-1.453	0.214	-
	(0.455)	(0.247)	**(0.012)**	(0.757)	(0.751)	(0.514)	(0.273)	(0.054)	(0.051)	(0.078)	(0.584)	-
ELNET, CV	-0.129	-0.699	**-2.384**	0.684	0.665	0.023	-0.615	-1.661	-1.689	-1.455	0.177	-0.301
	(0.449)	(0.245)	**(0.012)**	(0.750)	(0.745)	(0.509)	(0.272)	(0.054)	(0.051)	(0.078)	(0.570)	(0.383)
Ridge, AIC	-0.526	-1.006	**-2.531**	0.131	0.300	-0.367	-1.025	**-1.982**	**-1.988**	**-1.877**	-1.620	-0.848
	(0.301)	(0.161)	**(0.008)**	(0.552)	(0.617)	(0.358)	(0.157)	**(0.028)**	**(0.028)**	**(0.035)**	(0.058)	(0.202)
Lasso, AIC	-0.622	-1.107	**-2.550**	-0.143	0.026	-0.558	-1.219	**-2.123**	**-2.122**	**-2.089**	-1.234	-0.892
	(0.269)	(0.139)	**(0.008)**	(0.444)	(0.510)	(0.290)	(0.116)	**(0.021)**	**(0.021)**	**(0.023)**	(0.113)	(0.190)
ELNET, AIC	-0.556	-1.061	**-2.526**	0.011	0.233	-0.479	-1.161	**-2.075**	**-2.079**	**-2.030**	-1.063	-0.800
	(0.291)	(0.149)	**(0.009)**	(0.504)	(0.591)	(0.318)	(0.127)	**(0.023)**	**(0.023)**	**(0.026)**	(0.148)	(0.215)
k-NN	2.325	1.192	-0.999	2.254	2.030	1.458	0.949	0.086	-0.161	0.339	2.072	1.950
	(0.986)	(0.879)	(0.163)	(0.984)	(0.974)	(0.922)	(0.825)	(0.534)	(0.436)	(0.631)	(0.977)	(0.970)
wk-NN	2.540	1.294	-0.974	2.392	2.137	1.528	1.006	0.141	-0.116	0.400	2.210	2.084
	(0.992)	(0.897)	(0.169)	(0.988)	(0.980)	(0.932)	(0.839)	(0.556)	(0.454)	(0.654)	(0.983)	(0.977)
RF	0.853	-0.190	**-2.088**	1.263	1.093	0.472	-0.170	-1.256	-1.368	-0.996	1.120	1.142
	(0.800)	(0.425)	**(0.023)**	(0.892)	(0.858)	(0.680)	(0.433)	(0.109)	(0.091)	(0.164)	(0.864)	(0.869)
FFNN	0.785	0.008	**-2.245**	1.511	1.278	0.657	-0.027	-1.184	-1.360	-0.897	1.128	1.007
	(0.781)	(0.503)	**(0.016)**	(0.929)	(0.895)	(0.742)	(0.489)	(0.123)	(0.092)	(0.188)	(0.866)	(0.839)
RNN	1.167	0.487	-1.490	2.168	2.170	1.404	0.534	-0.709	-0.933	-0.468	1.577	1.326
	(0.874)	(0.685)	(0.073)	(0.981)	(0.981)	(0.915)	(0.701)	(0.242)	(0.179)	(0.322)	(0.937)	(0.903)
SVR-LIN	0.467	-0.335	**-2.162**	1.522	1.433	0.485	-0.341	-1.549	**-1.710**	-1.323	0.994	0.736
	(0.678)	(0.370)	**(0.019)**	(0.931)	(0.919)	(0.684)	(0.368)	(0.066)	**(0.049)**	(0.098)	(0.836)	(0.766)
SVR-POLY	1.212	1.022	-0.874	1.257	1.301	1.098	0.787	0.127	-0.068	0.319	1.138	1.107
	(0.882)	(0.843)	(0.194)	(0.891)	(0.898)	(0.859)	(0.781)	(0.550)	(0.473)	(0.624)	(0.868)	(0.861)
SVR-RBF	1.845	1.158	-0.562	1.895	1.733	1.399	0.970	0.374	0.156	0.566	1.714	1.683
	(0.963)	(0.872)	(0.289)	(0.966)	(0.953)	(0.914)	(0.830)	(0.645)	(0.561)	(0.712)	(0.952)	(0.949)
SVR-ANOVA	1.388	0.903	-1.381	2.067	1.902	1.535	0.825	-0.277	-0.612	0.032	1.568	1.524
	(0.912)	(0.813)	(0.089)	(0.976)	(0.967)	(0.932)	(0.792)	(0.392)	(0.273)	(0.513)	(0.936)	(0.931)
AR+SVR-POLY	0.581	0.193	-1.491	0.999	1.160	0.952	0.151	-0.756	-1.016	-0.579	0.777	0.734
	(0.717)	(0.576)	(0.073)	(0.837)	(0.872)	(0.826)	(0.559)	(0.228)	(0.159)	(0.283)	(0.778)	(0.766)
AR+SVR-RBF	0.674	-0.147	**-2.070**	1.833	1.345	0.593	-0.165	-1.500	-1.617	-1.249	0.952	0.810
	(0.747)	(0.442)	**(0.024)**	(0.962)	(0.906)	(0.721)	(0.435)	(0.072)	(0.058)	(0.111)	(0.826)	(0.788)
AR+SVR-ANOVA	-0.388	-0.901	**-2.444**	0.396	0.395	-0.321	-1.139	**-2.198**	**-2.272**	**-2.233**	-0.328	-0.373
	(0.350)	(0.187)	**(0.010)**	(0.653)	(0.652)	(0.375)	(0.132)	**(0.018)**	**(0.015)**	**(0.017)**	(0.373)	(0.356)
AR+FFNN	-0.473	-0.924	**-2.454**	1.029	0.379	-0.404	-1.157	**-2.182**	**-2.260**	**-2.226**	-0.536	-0.545
	(0.320)	(0.181)	**(0.010)**	(0.844)	(0.646)	(0.344)	(0.128)	**(0.019)**	**(0.016)**	**(0.017)**	(0.298)	(0.295)
AR+RNN	0.544	-0.001	**-1.947**	1.390	1.286	0.869	-0.039	-1.202	-1.380	-0.918	0.912	0.899
	(0.705)	(0.500)	**(0.030)**	(0.913)	(0.896)	(0.804)	(0.485)	(0.119)	(0.089)	(0.183)	(0.816)	(0.812)
Ave. BM	-0.029	-1.215	**-3.041**	0.589	0.582	0.087	-0.518	**-2.177**	**-1.853**	**-1.730**	0.181	0.097
	(0.488)	(0.117)	**(0.002)**	(0.720)	(0.718)	(0.534)	(0.304)	**(0.019)**	**(0.037)**	**(0.047)**	(0.571)	(0.538)
Ave. Linear	-0.383	-0.971	**-2.527**	0.483	0.692	-0.356	-1.176	**-2.374**	**-2.389**	**-2.495**	-0.333	-0.378
	(0.352)	(0.170)	**(0.009)**	(0.684)	(0.753)	(0.362)	(0.124)	**(0.012)**	**(0.012)**	**(0.009)**	(0.371)	(0.354)
Ave. Local	1.574	0.356	**-1.738**	1.568	1.336	0.799	0.240	-0.748	-0.916	-0.476	1.341	1.286
	(0.937)	(0.638)	**(0.046)**	(0.936)	(0.904)	(0.785)	(0.594)	(0.230)	(0.183)	(0.319)	(0.905)	(0.896)
Ave. Non-linear	0.274	-0.437	**-2.225**	1.295	0.932	0.274	-0.412	-1.653	**-1.782**	-1.455	0.518	0.386
	(0.607)	(0.332)	**(0.017)**	(0.897)	(0.821)	(0.607)	(0.342)	(0.054)	**(0.042)**	(0.078)	(0.696)	(0.649)
Ave. AR+	-0.299	-0.848	**-2.438**	0.791	0.685	-0.258	-0.973	**-2.106**	**-2.179**	**-2.048**	-0.234	-0.339
	(0.383)	(0.202)	**(0.010)**	(0.782)	(0.751)	(0.399)	(0.169)	**(0.022)**	**(0.019)**	**(0.025)**	(0.408)	(0.368)
Tot. Ave.	-0.613	-1.034	**-2.535**	0.253	0.227	-0.362	-1.000	**-2.227**	**-2.235**	**-2.168**	-0.602	-0.669
	(0.272)	(0.155)	**(0.008)**	(0.599)	(0.589)	(0.360)	(0.163)	**(0.017)**	**(0.017)**	**(0.019)**	(0.276)	(0.254)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.32: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 1$. $N = 31$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	0.129	0.526	0.622	0.556	**-2.325**	**-2.540**	-0.853	-0.785	-1.167	-0.467	-1.212	**-1.845**
	(0.551)	(0.699)	(0.731)	(0.709)	**(0.014)**	**(0.008)**	(0.200)	(0.219)	(0.126)	(0.322)	(0.118)	**(0.037)**
RW	0.699	1.006	1.107	1.061	-1.192	-1.294	0.190	-0.008	-0.487	0.335	-1.022	-1.158
	(0.755)	(0.839)	(0.861)	(0.851)	(0.121)	(0.103)	(0.575)	(0.497)	(0.315)	(0.630)	(0.157)	(0.128)
DDD	2.384	2.531	2.550	2.526	0.999	0.974	2.088	2.245	1.490	2.162	0.874	0.562
	(0.988)	(0.992)	(0.992)	(0.991)	(0.837)	(0.831)	(0.977)	(0.984)	(0.927)	(0.981)	(0.806)	(0.711)
AR(p)	-0.684	-0.131	0.143	-0.011	**-2.254**	**-2.392**	-1.263	-1.511	**-2.168**	-1.522	-1.257	**-1.895**
	(0.250)	(0.448)	(0.556)	(0.496)	**(0.016)**	**(0.012)**	(0.108)	(0.071)	**(0.019)**	(0.069)	(0.109)	**(0.034)**
GETS	-0.665	-0.300	-0.026	-0.233	**-2.030**	**-2.137**	-1.093	-1.278	**-2.170**	-1.433	-1.301	**-1.733**
	(0.255)	(0.383)	(0.490)	(0.409)	**(0.026)**	**(0.020)**	(0.142)	(0.105)	**(0.019)**	(0.081)	(0.102)	**(0.047)**
GETS-IIS	-0.023	0.367	0.558	0.479	-1.458	-1.528	-0.472	-0.657	-1.404	-0.485	-1.098	-1.399
	(0.491)	(0.642)	(0.710)	(0.682)	(0.078)	(0.068)	(0.320)	(0.258)	(0.085)	(0.316)	(0.141)	(0.086)
GETS-SIS	0.615	1.025	1.219	1.161	-0.949	-1.006	0.170	0.027	-0.534	0.341	-0.787	-0.970
	(0.728)	(0.843)	(0.884)	(0.873)	(0.175)	(0.161)	(0.567)	(0.511)	(0.299)	(0.632)	(0.219)	(0.170)
GETS-DDD	1.661	1.982	2.123	2.075	-0.086	-0.141	1.256	1.184	0.709	1.549	-0.127	-0.374
	(0.946)	(0.972)	(0.979)	(0.977)	(0.466)	(0.444)	(0.891)	(0.877)	(0.758)	(0.934)	(0.450)	(0.355)
GETS-IIS-DDD	1.689	1.988	2.122	2.079	0.161	0.116	1.368	1.360	0.933	1.710	0.068	-0.156
	(0.949)	(0.972)	(0.979)	(0.977)	(0.564)	(0.546)	(0.909)	(0.908)	(0.821)	(0.951)	(0.527)	(0.439)
GETS-SIS-DDD	1.455	1.877	2.089	2.030	-0.339	-0.400	0.996	0.897	0.468	1.323	-0.319	-0.566
	(0.922)	(0.965)	(0.977)	(0.974)	(0.369)	(0.346)	(0.836)	(0.812)	(0.678)	(0.902)	(0.376)	(0.288)
Ridge, CV	-0.177	1.620	1.234	1.063	**-2.072**	**-2.210**	-1.120	-1.128	-1.577	-0.994	-1.138	**-1.714**
	(0.430)	(0.942)	(0.887)	(0.852)	**(0.023)**	**(0.017)**	(0.136)	(0.134)	(0.063)	(0.164)	(0.132)	**(0.048)**
Lasso, CV	0.301	0.848	0.892	0.800	**-1.950**	**-2.084**	-1.142	-1.007	-1.326	-0.736	-1.107	-1.683
	(0.617)	(0.798)	(0.810)	(0.785)	**(0.030)**	**(0.023)**	(0.131)	(0.161)	(0.097)	(0.234)	(0.139)	(0.051)
ELNET, CV	-	0.801	0.855	0.762	**-1.976**	**-2.111**	-1.159	-1.028	-1.344	-0.758	-1.110	-1.693
	-	(0.785)	(0.800)	(0.774)	**(0.029)**	**(0.022)**	(0.128)	(0.156)	(0.094)	(0.227)	(0.138)	(0.050)
Ridge, AIC	-0.801	-	0.627	0.300	**-2.135**	**-2.268**	-1.354	-1.357	**-1.902**	-1.526	-1.247	**-1.780**
	(0.215)	-	(0.732)	(0.617)	**(0.021)**	**(0.015)**	(0.093)	(0.092)	**(0.033)**	(0.069)	(0.111)	**(0.043)**
Lasso, AIC	-0.855	-0.627	-	-0.888	**-2.128**	**-2.251**	-1.328	-1.359	**-2.117**	**-1.729**	-1.295	**-1.783**
	(0.200)	(0.268)	-	(0.191)	**(0.021)**	**(0.016)**	(0.097)	(0.092)	**(0.021)**	**(0.047)**	(0.103)	**(0.042)**
ELNET, AIC	-0.762	-0.300	0.888	-	**-2.088**	**-2.213**	-1.259	-1.296	**-2.059**	-1.623	-1.272	**-1.758**
	(0.226)	(0.383)	(0.809)	-	**(0.023)**	**(0.017)**	(0.109)	(0.102)	**(0.024)**	(0.057)	(0.107)	**(0.044)**
k-NN	1.976	2.135	2.128	2.088	-	-0.805	1.834	1.862	0.859	1.827	-0.053	-0.462
	(0.971)	(0.979)	(0.979)	(0.977)	-	(0.214)	(0.962)	(0.964)	(0.802)	(0.961)	(0.479)	(0.324)
wk-NN	2.111	2.268	2.251	2.213	0.805	-	2.002	2.063	0.936	1.970	-0.015	-0.403
	(0.978)	(0.985)	(0.984)	(0.983)	(0.786)	-	(0.973)	(0.976)	(0.822)	(0.971)	(0.494)	(0.345)
RF	1.159	1.354	1.328	1.259	**-1.834**	**-2.002**	-	-0.309	-0.756	0.280	-0.890	-1.603
	(0.872)	(0.907)	(0.903)	(0.891)	**(0.038)**	**(0.027)**	-	(0.380)	(0.228)	(0.609)	(0.190)	(0.060)
FFNN	1.028	1.357	1.359	1.296	**-1.862**	**-2.063**	0.309	-	-0.592	0.472	-0.790	-1.633
	(0.844)	(0.908)	(0.908)	(0.898)	**(0.036)**	**(0.024)**	(0.620)	-	(0.279)	(0.680)	(0.218)	(0.056)
RNN	1.344	1.902	2.117	2.059	-0.859	-0.936	0.756	0.592	-	1.139	-0.531	-0.912
	(0.906)	(0.967)	(0.979)	(0.976)	(0.198)	(0.178)	(0.772)	(0.721)	-	(0.868)	(0.300)	(0.184)
SVR-LIN	0.758	1.526	1.729	1.623	**-1.827**	**-1.970**	-0.280	-0.472	-1.139	-	-0.970	-1.562
	(0.773)	(0.931)	(0.953)	(0.943)	**(0.039)**	**(0.029)**	(0.391)	(0.320)	(0.132)	-	(0.170)	(0.064)
SVR-POLY	1.110	1.247	1.295	1.272	0.053	0.015	0.890	0.790	0.531	0.970	-	-0.178
	(0.862)	(0.889)	(0.897)	(0.893)	(0.521)	(0.506)	(0.810)	(0.782)	(0.700)	(0.830)	-	(0.430)
SVR-RBF	1.693	1.780	1.783	1.758	0.462	0.403	1.603	1.633	0.912	1.562	0.178	-
	(0.950)	(0.957)	(0.958)	(0.956)	(0.676)	(0.655)	(0.940)	(0.944)	(0.816)	(0.936)	(0.570)	-
SVR-ANOVA	1.529	1.757	1.838	1.794	-0.381	-0.453	1.083	1.342	0.429	1.203	-0.265	-0.659
	(0.932)	(0.955)	(0.962)	(0.959)	(0.353)	(0.327)	(0.856)	(0.905)	(0.665)	(0.881)	(0.397)	(0.257)
AR+SVR-POLY	0.739	0.990	1.105	1.061	-0.728	-0.779	0.324	0.159	-0.240	0.502	-0.658	-0.861
	(0.767)	(0.835)	(0.861)	(0.852)	(0.236)	(0.221)	(0.626)	(0.563)	(0.406)	(0.690)	(0.258)	(0.198)
AR+SVR-RBF	0.839	1.293	1.441	1.338	**-1.724**	**-1.870**	0.057	-0.240	-1.005	0.298	-0.863	-1.630
	(0.796)	(0.897)	(0.920)	(0.905)	**(0.047)**	**(0.036)**	(0.523)	(0.406)	(0.161)	(0.616)	(0.197)	(0.057)
AR+SVR-ANOVA	-0.358	0.119	0.327	0.216	**-2.042**	**-2.169**	-0.897	-1.185	**-1.984**	-1.014	-1.204	**-1.764**
	(0.362)	(0.547)	(0.627)	(0.585)	**(0.025)**	**(0.019)**	(0.188)	(0.123)	**(0.028)**	(0.159)	(0.119)	**(0.044)**
AR+FFNN	-0.524	0.042	0.329	0.172	**-2.182**	**-2.311**	-1.113	-1.368	**-2.126**	-1.327	-1.230	**-1.841**
	(0.302)	(0.517)	(0.628)	(0.568)	**(0.019)**	**(0.014)**	(0.137)	(0.091)	**(0.021)**	(0.097)	(0.114)	**(0.038)**
AR+RNN	0.914	1.179	1.243	1.199	-1.132	-1.222	0.201	-0.011	-0.579	0.388	-0.755	-1.247
	(0.816)	(0.876)	(0.888)	(0.880)	(0.133)	(0.116)	(0.579)	(0.496)	(0.284)	(0.650)	(0.228)	(0.111)
Ave. BM	0.112	0.541	0.655	0.588	**-1.956**	**-2.126**	-0.642	-0.845	-1.182	-0.430	-1.249	-1.694
	(0.544)	(0.704)	(0.741)	(0.719)	**(0.030)**	**(0.021)**	(0.263)	(0.202)	(0.123)	(0.335)	(0.111)	(0.050)
Ave. Linear	-0.358	0.196	0.556	0.385	**-1.956**	**-2.076**	-0.927	-1.120	**-1.973**	-1.190	-1.240	**-1.710**
	(0.362)	(0.577)	(0.709)	(0.648)	**(0.030)**	**(0.023)**	(0.181)	(0.136)	**(0.029)**	(0.122)	(0.112)	**(0.049)**
Ave. Local	1.313	1.460	1.457	1.413	**-2.832**	**-3.326**	0.961	0.629	-0.159	0.912	-0.617	-1.440
	(0.900)	(0.923)	(0.922)	(0.916)	**(0.004)**	**(0.001)**	(0.828)	(0.733)	(0.437)	(0.816)	(0.271)	(0.080)
Ave. Non-linear	0.404	0.891	1.019	0.935	**-2.294**	**-2.488**	-0.470	-0.891	-1.453	-0.254	-1.015	**-1.954**
	(0.655)	(0.810)	(0.842)	(0.821)	**(0.014)**	**(0.009)**	(0.321)	(0.190)	(0.078)	(0.401)	(0.159)	**(0.030)**
Ave. AR+	-0.320	0.318	0.594	0.453	**-1.941**	**-2.060**	-0.918	-1.157	**-1.894**	-1.079	-1.184	**-1.736**
	(0.376)	(0.624)	(0.722)	(0.673)	**(0.031)**	**(0.024)**	(0.183)	(0.128)	**(0.034)**	(0.145)	(0.123)	**(0.046)**
Tot. Ave.	-0.648	-0.008	0.244	0.107	**-2.349**	**-2.507**	-1.384	-1.542	**-2.177**	-1.631	-1.255	**-1.950**
	(0.261)	(0.497)	(0.596)	(0.542)	**(0.013)**	**(0.009)**	(0.088)	(0.067)	**(0.019)**	(0.057)	(0.110)	**(0.030)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.33: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 1$. $N = 31$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.388	-0.581	-0.674	0.388	0.473	-0.544	0.029	0.383	-1.574	-0.274	0.299	0.613
	(0.088)	(0.283)	(0.253)	(0.650)	(0.680)	(0.295)	(0.512)	(0.648)	(0.063)	(0.393)	(0.617)	(0.728)
RW	-0.903	-0.193	0.147	0.901	0.924	0.001	1.215	0.971	-0.356	0.437	0.848	1.034
	(0.187)	(0.424)	(0.558)	(0.813)	(0.819)	(0.500)	(0.883)	(0.830)	(0.362)	(0.668)	(0.798)	(0.845)
DDD	1.381	1.491	2.070	2.444	2.454	1.947	3.041	2.527	1.738	2.225	2.438	2.535
	(0.911)	(0.927)	(0.976)	(0.990)	(0.990)	(0.970)	(0.998)	(0.991)	(0.954)	(0.983)	(0.990)	(0.992)
AR(p)	**-2.067**	-0.999	**-1.833**	-0.396	-1.029	-1.390	-0.589	-0.483	-1.568	-1.295	-0.791	-0.253
	(0.024)	(0.163)	**(0.038)**	(0.347)	(0.156)	(0.087)	(0.280)	(0.316)	(0.064)	(0.103)	(0.218)	(0.401)
GETS	**-1.902**	-1.160	-1.345	-0.395	-0.379	-1.286	-0.582	-0.692	-1.336	-0.932	-0.685	-0.227
	(0.033)	(0.128)	(0.094)	(0.348)	(0.354)	(0.104)	(0.282)	(0.247)	(0.096)	(0.179)	(0.249)	(0.411)
GETS-IIS	-1.535	-0.952	-0.593	0.321	0.404	-0.869	-0.087	0.356	-0.799	-0.274	0.258	0.362
	(0.068)	(0.174)	(0.279)	(0.625)	(0.656)	(0.196)	(0.466)	(0.638)	(0.215)	(0.393)	(0.601)	(0.640)
GETS-SIS	-0.825	-0.151	0.165	1.139	1.157	0.039	0.518	1.176	-0.240	0.412	0.973	1.000
	(0.208)	(0.441)	(0.565)	(0.868)	(0.872)	(0.515)	(0.696)	(0.876)	(0.406)	(0.658)	(0.831)	(0.837)
GETS-DDD	0.277	0.756	1.500	2.198	2.182	1.202	2.177	2.374	0.748	1.653	2.106	2.227
	(0.608)	(0.772)	(0.928)	(0.982)	(0.981)	(0.881)	(0.981)	(0.988)	(0.770)	(0.946)	(0.978)	(0.983)
GETS-IIS-DDD	0.612	1.016	1.617	2.272	2.260	1.380	1.853	2.389	0.916	1.782	2.179	2.235
	(0.727)	(0.841)	(0.942)	(0.985)	(0.984)	(0.911)	(0.963)	(0.988)	(0.817)	(0.958)	(0.981)	(0.983)
GETS-SIS-DDD	-0.032	0.579	1.249	2.233	2.226	0.918	1.730	2.495	0.476	1.455	2.048	2.168
	(0.487)	(0.717)	(0.889)	(0.983)	(0.983)	(0.817)	(0.953)	(0.991)	(0.681)	(0.922)	(0.975)	(0.981)
Ridge, CV	-1.568	-0.777	-0.952	0.328	0.536	-0.912	-0.181	0.333	-1.341	-0.518	0.234	0.602
	(0.064)	(0.222)	(0.174)	(0.627)	(0.702)	(0.184)	(0.429)	(0.629)	(0.095)	(0.304)	(0.592)	(0.724)
Lasso, CV	-1.524	-0.734	-0.810	0.373	0.545	-0.899	-0.097	0.378	-1.286	-0.386	0.339	0.669
	(0.069)	(0.234)	(0.212)	(0.644)	(0.705)	(0.188)	(0.462)	(0.646)	(0.104)	(0.351)	(0.632)	(0.746)
ELNET, CV	-1.529	-0.739	-0.839	0.358	0.524	-0.914	-0.112	0.358	-1.313	-0.404	0.320	0.648
	(0.068)	(0.233)	(0.204)	(0.638)	(0.698)	(0.184)	(0.456)	(0.638)	(0.100)	(0.345)	(0.624)	(0.739)
Ridge, AIC	**-1.757**	-0.990	-1.293	-0.119	-0.042	-1.179	-0.541	-0.196	-1.460	-0.891	-0.318	0.008
	(0.045)	(0.165)	(0.103)	(0.453)	(0.483)	(0.124)	(0.296)	(0.423)	(0.077)	(0.190)	(0.376)	(0.503)
Lasso, AIC	**-1.838**	-1.105	-1.441	-0.327	-0.329	-1.243	-0.655	-0.556	-1.457	-1.019	-0.594	-0.244
	(0.038)	(0.139)	(0.080)	(0.373)	(0.372)	(0.112)	(0.259)	(0.291)	(0.078)	(0.158)	(0.278)	(0.404)
ELNET, AIC	**-1.794**	-1.061	-1.338	-0.216	-0.172	-1.199	-0.588	-0.385	-1.413	-0.935	-0.453	-0.107
	(0.041)	(0.148)	(0.095)	(0.415)	(0.432)	(0.120)	(0.281)	(0.352)	(0.084)	(0.179)	(0.327)	(0.458)
k-NN	0.381	0.728	1.724	2.042	2.182	1.132	1.956	1.956	2.832	2.294	1.941	2.349
	(0.647)	(0.764)	(0.953)	(0.975)	(0.981)	(0.867)	(0.970)	(0.970)	(0.996)	(0.986)	(0.969)	(0.987)
wk-NN	0.453	0.779	1.870	2.169	2.311	1.222	2.126	2.076	3.326	2.488	2.060	2.507
	(0.673)	(0.779)	(0.964)	(0.981)	(0.986)	(0.884)	(0.979)	(0.977)	(0.999)	(0.991)	(0.976)	(0.991)
RF	-1.083	-0.324	-0.057	0.897	1.113	-0.201	0.642	0.927	-0.961	0.470	0.918	1.384
	(0.144)	(0.374)	(0.477)	(0.812)	(0.863)	(0.421)	(0.737)	(0.819)	(0.172)	(0.679)	(0.817)	(0.912)
FFNN	-1.342	-0.159	0.240	1.185	1.368	0.011	0.845	1.120	-0.629	0.891	1.157	1.542
	(0.095)	(0.437)	(0.594)	(0.877)	(0.909)	(0.504)	(0.798)	(0.864)	(0.267)	(0.810)	(0.872)	(0.933)
RNN	-0.429	0.240	1.005	1.984	2.126	0.579	1.182	1.973	0.159	1.453	1.894	2.177
	(0.335)	(0.594)	(0.839)	(0.972)	(0.979)	(0.716)	(0.877)	(0.971)	(0.563)	(0.922)	(0.966)	(0.981)
SVR-LIN	-1.203	-0.502	-0.298	1.014	1.327	-0.388	0.430	1.190	-0.912	0.254	1.079	1.631
	(0.119)	(0.310)	(0.384)	(0.841)	(0.903)	(0.350)	(0.665)	(0.878)	(0.184)	(0.599)	(0.855)	(0.943)
SVR-POLY	0.265	0.658	0.863	1.204	1.230	0.755	1.249	1.240	0.617	1.015	1.184	1.255
	(0.603)	(0.742)	(0.803)	(0.881)	(0.886)	(0.772)	(0.889)	(0.888)	(0.729)	(0.841)	(0.877)	(0.890)
SVR-RBF	0.659	0.861	1.630	1.764	1.841	1.247	1.694	1.710	1.440	1.954	1.736	1.950
	(0.743)	(0.802)	(0.943)	(0.956)	(0.962)	(0.889)	(0.950)	(0.951)	(0.920)	(0.970)	(0.954)	(0.970)
SVR-ANOVA	-	0.573	1.193	1.914	2.024	0.936	1.539	1.864	0.600	1.612	1.852	2.023
	-	(0.714)	(0.879)	(0.967)	(0.974)	(0.822)	(0.933)	(0.964)	(0.724)	(0.941)	(0.963)	(0.974)
AR+SVR-POLY	-0.573	-	0.283	0.908	0.955	0.174	0.617	0.975	-0.101	0.504	0.952	0.968
	(0.286)	-	(0.610)	(0.815)	(0.827)	(0.569)	(0.729)	(0.831)	(0.460)	(0.691)	(0.826)	(0.830)
AR+SVR-RBF	-1.193	-0.283	-	1.337	1.617	-0.176	0.671	1.279	-0.743	0.787	1.306	2.058
	(0.121)	(0.390)	-	(0.904)	(0.942)	(0.431)	(0.746)	(0.895)	(0.232)	(0.781)	(0.899)	(0.976)
AR+SVR-ANOVA	**-1.914**	-0.908	-1.337	-	0.162	-1.284	-0.412	-0.061	-1.312	-0.816	-0.253	0.181
	(0.033)	(0.185)	(0.096)	-	(0.564)	(0.105)	(0.342)	(0.476)	(0.100)	(0.210)	(0.401)	(0.571)
AR+FFNN	**-2.024**	-0.955	-1.617	-0.162	-	-1.283	-0.477	-0.249	-1.467	-1.099	-0.485	0.088
	(0.026)	(0.173)	(0.058)	(0.436)	-	(0.105)	(0.318)	(0.403)	(0.076)	(0.140)	(0.316)	(0.535)
AR+RNN	-0.936	-0.174	0.176	1.284	1.283	-	0.625	1.144	-0.355	0.519	1.381	1.301
	(0.178)	(0.431)	(0.569)	(0.895)	(0.895)	-	(0.732)	(0.869)	(0.363)	(0.696)	(0.911)	(0.898)
Ave. BM	-1.539	-0.617	-0.671	0.412	0.477	-0.625	-	0.429	-1.187	-0.253	0.321	0.604
	(0.067)	(0.271)	(0.254)	(0.658)	(0.682)	(0.268)	-	(0.664)	(0.122)	(0.401)	(0.625)	(0.725)
Ave. Linear	**-1.864**	-0.975	-1.279	0.061	0.249	-1.144	-0.429	-	-1.244	-0.762	-0.193	0.250
	(0.036)	(0.169)	(0.105)	(0.524)	(0.597)	(0.131)	(0.336)	-	(0.112)	(0.226)	(0.424)	(0.598)
Ave. Local	-0.600	0.101	0.743	1.312	1.467	0.355	1.187	1.244	-	1.375	1.245	1.687
	(0.276)	(0.540)	(0.768)	(0.900)	(0.924)	(0.637)	(0.878)	(0.888)	-	(0.910)	(0.889)	(0.949)
Ave. Non-linear	-1.612	-0.504	-0.787	0.816	1.099	-0.519	0.253	0.762	-1.375	-	0.742	1.572
	(0.059)	(0.309)	(0.219)	(0.790)	(0.860)	(0.304)	(0.599)	(0.774)	(0.090)	-	(0.768)	(0.937)
Ave. AR+	**-1.852**	-0.952	-1.306	0.253	0.485	-1.381	-0.321	0.193	-1.245	-0.742	-	0.491
	(0.037)	(0.174)	(0.101)	(0.599)	(0.684)	(0.089)	(0.375)	(0.576)	(0.111)	(0.232)	-	(0.687)
Tot. Ave.	**-2.023**	-0.968	**-2.058**	-0.181	-0.088	-1.301	-0.604	-0.250	-1.687	-1.572	-0.491	-
	(0.026)	(0.170)	**(0.024)**	(0.429)	(0.465)	(0.102)	(0.275)	(0.402)	(0.051)	(0.063)	(0.313)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.34: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 2$. $N = 30$.

	AR(1)	RW	DDD	AR(p)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.367	-0.692	0.120	0.282	0.056	-0.126	-1.252	-1.445	-1.226	**-2.453**	**-2.604**
	-	(0.358)	(0.247)	(0.547)	(0.610)	(0.522)	(0.450)	(0.110)	(0.080)	(0.115)	**(0.010)**	**(0.007)**
RW	0.367	-	-1.441	0.621	0.709	0.582	0.275	**-1.708**	**-1.836**	-1.667	-0.581	-0.617
	(0.642)	-	(0.080)	(0.730)	(0.758)	(0.717)	(0.607)	**(0.049)**	**(0.038)**	(0.053)	(0.283)	(0.271)
DDD	0.692	1.441	-	1.016	1.062	1.017	0.697	-1.346	-1.577	-1.165	-0.145	-0.168
	(0.753)	(0.920)	-	(0.841)	(0.852)	(0.841)	(0.754)	(0.094)	(0.063)	(0.127)	(0.443)	(0.434)
AR(p)	-0.120	-0.621	-1.016	-	2.177	-0.074	-0.287	-1.490	-1.642	-1.449	-1.648	**-1.846**
	(0.453)	(0.270)	(0.159)	-	(0.981)	(0.471)	(0.388)	(0.073)	(0.056)	(0.079)	(0.055)	**(0.038)**
GETS	-0.282	-0.709	-1.062	**-2.177**	-	-0.486	-0.457	-1.549	-1.696	-1.517	-1.672	**-1.846**
	(0.390)	(0.242)	(0.148)	**(0.019)**	-	(0.315)	(0.326)	(0.066)	(0.050)	(0.070)	(0.053)	**(0.038)**
GETS-IIS	-0.056	-0.582	-1.017	0.074	0.486	-	-0.282	-1.514	-1.667	-1.461	-1.235	-1.348
	(0.478)	(0.283)	(0.159)	(0.529)	(0.685)	-	(0.390)	(0.070)	(0.053)	(0.077)	(0.113)	(0.094)
GETS-SIS	0.126	-0.275	-0.697	0.287	0.457	0.282	-	-1.504	**-1.719**	-1.479	-0.751	-0.811
	(0.550)	(0.393)	(0.246)	(0.612)	(0.674)	(0.610)	-	(0.072)	**(0.048)**	(0.075)	(0.229)	(0.212)
GETS-DDD	1.252	1.708	1.346	1.490	1.549	1.514	1.504	-	**-2.291**	1.532	0.438	0.439
	(0.890)	(0.951)	(0.906)	(0.927)	(0.934)	(0.930)	(0.928)	-	**(0.015)**	(0.932)	(0.668)	(0.668)
GETS-IIS-DDD	1.445	1.836	1.577	1.642	1.696	1.667	1.719	2.291	-	2.196	0.669	0.681
	(0.920)	(0.962)	(0.937)	(0.944)	(0.950)	(0.947)	(0.952)	(0.985)	-	(0.982)	(0.746)	(0.749)
GETS-SIS-DDD	1.226	1.667	1.165	1.449	1.517	1.461	1.479	-1.532	**-2.196**	-	0.353	0.351
	(0.885)	(0.947)	(0.873)	(0.921)	(0.930)	(0.923)	(0.925)	(0.068)	**(0.018)**	-	(0.637)	(0.636)
Ridge, CV	2.453	0.581	0.145	1.648	1.672	1.235	0.751	-0.438	-0.669	-0.353	-	-0.385
	(0.990)	(0.717)	(0.557)	(0.945)	(0.947)	(0.887)	(0.771)	(0.332)	(0.254)	(0.363)	-	(0.351)
Lasso, CV	2.604	0.617	0.168	1.846	1.846	1.348	0.811	-0.439	-0.681	-0.351	0.385	-
	(0.993)	(0.729)	(0.566)	(0.962)	(0.962)	(0.906)	(0.788)	(0.332)	(0.251)	(0.364)	(0.649)	-
ELNET, CV	2.600	0.610	0.158	1.805	1.806	1.319	0.794	-0.450	-0.693	-0.362	0.153	-0.424
	(0.993)	(0.727)	(0.562)	(0.959)	(0.959)	(0.901)	(0.783)	(0.328)	(0.247)	(0.360)	(0.560)	(0.337)
Ridge, AIC	0.113	-0.470	-0.942	0.887	1.428	0.389	-0.088	-1.399	-1.554	-1.345	-1.393	-1.541
	(0.545)	(0.321)	(0.177)	(0.809)	(0.918)	(0.650)	(0.465)	(0.086)	(0.066)	(0.095)	(0.087)	(0.067)
Lasso, AIC	0.019	-0.466	-0.859	0.569	1.009	0.161	-0.152	-1.342	-1.505	-1.297	**-1.754**	**-1.963**
	(0.507)	(0.322)	(0.199)	(0.713)	(0.839)	(0.564)	(0.440)	(0.095)	(0.072)	(0.102)	**(0.045)**	**(0.030)**
ELNET, AIC	0.183	-0.362	-0.779	1.159	1.444	0.387	-0.050	-1.284	-1.453	-1.235	-1.643	**-1.845**
	(0.572)	(0.360)	(0.221)	(0.872)	(0.920)	(0.649)	(0.480)	(0.105)	(0.078)	(0.113)	(0.056)	**(0.038)**
k-NN	2.513	1.528	1.042	2.357	2.424	2.073	1.706	0.418	0.164	0.531	1.521	1.462
	(0.991)	(0.931)	(0.847)	(0.987)	(0.989)	(0.976)	(0.951)	(0.661)	(0.564)	(0.700)	(0.930)	(0.923)
wk-NN	2.117	1.255	0.854	1.978	2.047	1.767	1.472	0.308	0.077	0.408	1.263	1.214
	(0.979)	(0.890)	(0.800)	(0.971)	(0.975)	(0.956)	(0.924)	(0.620)	(0.530)	(0.657)	(0.892)	(0.883)
RF	1.009	0.098	-0.316	1.109	1.158	0.747	0.347	-0.969	-1.206	-0.919	-1.167	-1.296
	(0.839)	(0.539)	(0.377)	(0.862)	(0.872)	(0.770)	(0.634)	(0.170)	(0.119)	(0.183)	(0.126)	(0.103)
FFNN	0.738	-0.063	-0.536	1.152	1.320	0.707	0.198	-1.057	-1.243	-0.987	**-1.861**	**-2.298**
	(0.767)	(0.475)	(0.298)	(0.871)	(0.901)	(0.757)	(0.578)	(0.150)	(0.112)	(0.166)	**(0.036)**	**(0.014)**
RNN	2.477	1.509	1.089	2.806	2.835	2.627	1.692	0.425	0.168	0.533	2.034	2.032
	(0.990)	(0.929)	(0.857)	(0.996)	(0.996)	(0.993)	(0.949)	(0.663)	(0.566)	(0.701)	(0.974)	(0.974)
SVR-LIN	-0.052	-0.518	-0.913	0.143	0.684	0.042	-0.227	-1.329	-1.479	-1.273	-1.446	-1.569
	(0.479)	(0.304)	(0.184)	(0.557)	(0.750)	(0.517)	(0.411)	(0.097)	(0.075)	(0.107)	(0.079)	(0.064)
SVR-POLY	0.577	-0.136	-0.555	0.849	1.098	0.518	0.150	-1.091	-1.275	-1.034	-1.320	-1.419
	(0.716)	(0.446)	(0.292)	(0.798)	(0.859)	(0.696)	(0.559)	(0.142)	(0.106)	(0.155)	(0.099)	(0.083)
SVR-RBF	2.297	0.882	0.448	1.844	1.892	1.492	1.078	-0.140	-0.380	-0.044	0.878	0.802
	(0.985)	(0.807)	(0.671)	(0.962)	(0.966)	(0.927)	(0.855)	(0.445)	(0.354)	(0.483)	(0.806)	(0.785)
SVR-ANOVA	1.808	1.586	0.922	2.852	2.477	2.546	1.317	0.041	-0.304	0.192	0.958	0.900
	(0.960)	(0.938)	(0.818)	(0.996)	(0.990)	(0.992)	(0.901)	(0.516)	(0.382)	(0.575)	(0.827)	(0.812)
AR+SVR-POLY	2.102	0.517	0.010	2.278	2.264	1.502	0.764	-0.629	-0.866	-0.542	-0.552	-0.747
	(0.978)	(0.696)	(0.504)	(0.985)	(0.984)	(0.928)	(0.774)	(0.267)	(0.197)	(0.296)	(0.293)	(0.231)
AR+SVR-RBF	0.834	0.288	-0.162	1.292	1.534	1.155	0.652	-0.770	-0.986	-0.686	-0.440	-0.492
	(0.794)	(0.612)	(0.436)	(0.897)	(0.932)	(0.871)	(0.740)	(0.224)	(0.166)	(0.249)	(0.331)	(0.313)
AR+SVR-ANOVA	-0.273	-1.234	-1.427	-0.314	-0.079	-0.352	-0.531	**-1.788**	**-1.894**	**-1.776**	-1.324	-1.432
	(0.393)	(0.114)	(0.082)	(0.378)	(0.469)	(0.364)	(0.300)	**(0.042)**	**(0.034)**	**(0.043)**	(0.098)	(0.081)
AR+FFNN	1.276	0.564	0.106	1.652	1.698	1.410	0.718	-0.457	-0.665	-0.372	-0.113	-0.157
	(0.894)	(0.711)	(0.542)	(0.945)	(0.950)	(0.915)	(0.761)	(0.325)	(0.256)	(0.356)	(0.455)	(0.438)
AR+RNN	1.624	1.445	0.888	2.084	2.101	2.136	1.263	0.045	-0.200	0.146	0.780	0.759
	(0.942)	(0.920)	(0.809)	(0.977)	(0.978)	(0.979)	(0.892)	(0.518)	(0.422)	(0.558)	(0.779)	(0.773)
Ave. BM	-0.573	-1.540	-1.677	-0.756	-0.486	-0.630	-0.819	**-2.268**	**-2.333**	**-2.365**	-1.500	-1.603
	(0.286)	(0.067)	(0.052)	(0.228)	(0.315)	(0.267)	(0.210)	**(0.015)**	**(0.013)**	**(0.012)**	(0.072)	(0.060)
Ave. Linear	-0.031	-0.597	-1.029	0.148	0.453	0.062	-0.255	**-1.778**	**-1.938**	**-1.789**	-1.316	-1.466
	(0.488)	(0.277)	(0.156)	(0.558)	(0.673)	(0.524)	(0.400)	**(0.043)**	**(0.031)**	**(0.042)**	(0.099)	(0.077)
Ave. Local	2.019	0.836	0.391	1.799	1.881	1.466	1.080	-0.196	-0.432	-0.102	0.552	0.504
	(0.974)	(0.795)	(0.651)	(0.959)	(0.965)	(0.923)	(0.855)	(0.423)	(0.335)	(0.460)	(0.708)	(0.691)
Ave. Non-linear	1.017	0.126	-0.308	1.488	1.547	0.932	0.366	-0.849	-1.048	-0.780	-1.426	-1.540
	(0.841)	(0.550)	(0.380)	(0.926)	(0.934)	(0.821)	(0.641)	(0.201)	(0.152)	(0.221)	(0.082)	(0.067)
Ave. AR+	0.576	-0.021	-0.486	1.313	1.477	0.934	0.245	-0.983	-1.166	-0.912	-1.214	-1.334
	(0.715)	(0.492)	(0.315)	(0.900)	(0.925)	(0.821)	(0.596)	(0.167)	(0.127)	(0.185)	(0.117)	(0.096)
Tot. Ave.	0.256	-0.327	-0.736	1.141	1.411	0.356	-0.032	-1.288	-1.467	-1.246	-1.692	**-1.905**
	(0.600)	(0.373)	(0.234)	(0.868)	(0.916)	(0.638)	(0.488)	(0.104)	(0.077)	(0.111)	(0.051)	**(0.033)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.35: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 2$. $N = 30$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	**-2.600**	-0.113	-0.019	-0.183	**-2.513**	**-2.117**	-1.009	-0.738	**-2.477**	0.052	-0.577	**-2.297**
	(0.007)	(0.455)	(0.493)	(0.428)	**(0.009)**	**(0.021)**	(0.161)	(0.233)	**(0.010)**	(0.521)	(0.284)	**(0.015)**
RW	-0.610	0.470	0.466	0.362	-1.528	-1.255	-0.098	0.063	-1.509	0.518	0.136	-0.882
	(0.273)	(0.679)	(0.678)	(0.640)	(0.069)	(0.110)	(0.461)	(0.525)	(0.071)	(0.696)	(0.554)	(0.193)
DDD	-0.158	0.942	0.859	0.779	-1.042	-0.854	0.316	0.536	-1.089	0.913	0.555	-0.448
	(0.438)	(0.823)	(0.801)	(0.779)	(0.153)	(0.200)	(0.623)	(0.702)	(0.143)	(0.816)	(0.708)	(0.329)
AR(p)	**-1.805**	-0.887	-0.569	-1.159	**-2.357**	**-1.978**	-1.109	-1.152	**-2.806**	-0.143	-0.849	**-1.844**
	(0.041)	(0.191)	(0.287)	(0.128)	**(0.013)**	**(0.029)**	(0.138)	(0.129)	**(0.004)**	(0.443)	(0.202)	**(0.038)**
GETS	**-1.806**	-1.428	-1.009	-1.444	**-2.424**	**-2.047**	-1.158	-1.320	**-2.835**	-0.684	-1.098	**-1.892**
	(0.041)	(0.082)	(0.161)	(0.080)	**(0.011)**	**(0.025)**	(0.128)	(0.099)	**(0.004)**	(0.250)	(0.141)	**(0.034)**
GETS-IIS	-1.319	-0.389	-0.161	-0.387	**-2.073**	**-1.767**	-0.747	-0.707	**-2.627**	-0.042	-0.518	-1.492
	(0.099)	(0.350)	(0.436)	(0.351)	**(0.024)**	**(0.044)**	(0.230)	(0.243)	**(0.007)**	(0.483)	(0.304)	(0.073)
GETS-SIS	-0.794	0.088	0.152	0.050	**-1.706**	-1.472	-0.347	-0.198	-1.692	0.227	-0.150	-1.078
	(0.217)	(0.535)	(0.560)	(0.520)	**(0.049)**	(0.076)	(0.366)	(0.422)	(0.051)	(0.589)	(0.441)	(0.145)
GETS-DDD	0.450	1.399	1.342	1.284	-0.418	-0.308	0.969	1.057	-0.425	1.329	1.091	0.140
	(0.672)	(0.914)	(0.905)	(0.895)	(0.339)	(0.380)	(0.830)	(0.850)	(0.337)	(0.903)	(0.858)	(0.555)
GETS-IIS-DDD	0.693	1.554	1.505	1.453	-0.164	-0.077	1.206	1.243	-0.168	1.479	1.275	0.380
	(0.753)	(0.934)	(0.928)	(0.922)	(0.436)	(0.470)	(0.881)	(0.888)	(0.434)	(0.925)	(0.894)	(0.646)
GETS-SIS-DDD	0.362	1.345	1.297	1.235	-0.531	-0.408	0.919	0.987	-0.533	1.273	1.034	0.044
	(0.640)	(0.905)	(0.898)	(0.887)	(0.300)	(0.343)	(0.817)	(0.834)	(0.299)	(0.893)	(0.845)	(0.517)
Ridge, CV	-0.153	1.393	1.754	1.643	-1.521	-1.263	1.167	1.861	**-2.034**	1.446	1.320	-0.878
	(0.440)	(0.913)	(0.955)	(0.944)	(0.070)	(0.108)	(0.874)	(0.964)	**(0.026)**	(0.921)	(0.901)	(0.194)
Lasso, CV	0.424	1.541	1.963	1.845	-1.462	-1.214	1.296	2.298	**-2.032**	1.569	1.419	-0.802
	(0.663)	(0.933)	(0.970)	(0.962)	(0.077)	(0.117)	(0.897)	(0.986)	**(0.026)**	(0.936)	(0.917)	(0.215)
ELNET, CV	-	1.509	1.913	1.794	-1.457	-1.206	1.244	2.199	**-2.003**	1.525	1.369	-0.820
	-	(0.929)	(0.967)	(0.958)	(0.078)	(0.119)	(0.888)	(0.982)	**(0.027)**	(0.931)	(0.909)	(0.209)
Ridge, AIC	-1.509	-	0.318	-0.135	**-2.239**	**-1.866**	-0.812	-0.667	**-2.719**	0.441	-0.444	-1.604
	(0.071)	-	(0.624)	(0.447)	**(0.017)**	**(0.036)**	(0.212)	(0.255)	**(0.005)**	(0.669)	(0.330)	(0.060)
Lasso, AIC	**-1.913**	-0.318	-	**-2.505**	**-2.407**	**-2.021**	-1.133	-1.201	**-3.063**	0.198	-0.693	**-1.849**
	(0.033)	(0.376)	-	**(0.009)**	**(0.011)**	**(0.026)**	(0.133)	(0.120)	**(0.002)**	(0.578)	(0.247)	**(0.037)**
ELNET, AIC	**-1.794**	0.135	2.505	-	**-2.348**	**-1.969**	-0.954	-0.900	**-2.998**	0.559	-0.467	**-1.764**
	(0.042)	(0.553)	(0.991)	-	**(0.013)**	**(0.029)**	(0.174)	(0.188)	**(0.003)**	(0.710)	(0.322)	**(0.044)**
k-NN	1.457	2.239	2.407	2.348	-	0.577	2.090	2.224	-0.002	2.418	2.489	0.937
	(0.922)	(0.983)	(0.989)	(0.987)	-	(0.716)	(0.977)	(0.983)	(0.499)	(0.989)	(0.991)	(0.822)
wk-NN	1.206	1.866	2.021	1.969	-0.577	-	1.788	1.843	-0.161	2.033	2.065	0.742
	(0.881)	(0.964)	(0.974)	(0.971)	(0.284)	-	(0.958)	(0.962)	(0.437)	(0.974)	(0.976)	(0.768)
RF	-1.244	0.812	1.133	0.954	**-2.090**	**-1.788**	-	0.354	**-2.454**	0.941	0.421	-1.288
	(0.112)	(0.788)	(0.867)	(0.826)	**(0.023)**	**(0.042)**	-	(0.637)	**(0.010)**	(0.823)	(0.662)	(0.104)
FFNN	**-2.199**	0.667	1.201	0.900	**-2.224**	**-1.843**	-0.354	-	**-3.118**	0.810	0.160	**-1.792**
	(0.018)	(0.745)	(0.880)	(0.812)	**(0.017)**	**(0.038)**	(0.363)	-	**(0.002)**	(0.788)	(0.563)	**(0.042)**
RNN	2.003	2.719	3.063	2.998	0.002	0.161	2.454	3.118	-	2.846	2.360	1.064
	(0.973)	(0.995)	(0.998)	(0.997)	(0.501)	(0.563)	(0.990)	(0.998)	-	(0.996)	(0.987)	(0.852)
SVR-LIN	-1.525	-0.441	-0.198	-0.559	**-2.418**	**-2.033**	-0.941	-0.810	**-2.846**	-	-0.792	**-1.726**
	(0.069)	(0.331)	(0.422)	(0.290)	**(0.011)**	**(0.026)**	(0.177)	(0.212)	**(0.004)**	-	(0.217)	**(0.047)**
SVR-POLY	-1.369	0.444	0.693	0.467	**-2.489**	**-2.065**	-0.421	-0.160	**-2.360**	0.792	-	**-2.019**
	(0.091)	(0.670)	(0.753)	(0.678)	**(0.009)**	**(0.024)**	(0.338)	(0.437)	**(0.013)**	(0.783)	-	**(0.026)**
SVR-RBF	0.820	1.604	1.849	1.764	-0.937	-0.742	1.288	1.792	-1.064	1.726	2.019	-
	(0.791)	(0.940)	(0.963)	(0.956)	(0.178)	(0.232)	(0.896)	(0.958)	(0.148)	(0.953)	(0.974)	-
SVR-ANOVA	0.935	2.914	2.928	2.759	-0.489	-0.359	1.680	3.046	-1.048	2.766	1.674	0.243
	(0.821)	(0.997)	(0.997)	(0.995)	(0.314)	(0.361)	(0.948)	(0.998)	(0.152)	(0.995)	(0.948)	(0.595)
AR+SVR-POLY	-0.690	1.738	2.430	2.214	-1.627	-1.342	0.975	2.364	**-2.213**	1.824	1.493	-1.127
	(0.248)	(0.954)	(0.989)	(0.983)	(0.057)	(0.095)	(0.831)	(0.987)	**(0.017)**	(0.961)	(0.927)	(0.135)
AR+SVR-RBF	-0.469	1.028	1.136	1.000	-1.575	-1.346	0.250	0.535	**-1.802**	1.318	1.035	-1.121
	(0.321)	(0.844)	(0.867)	(0.837)	(0.063)	(0.094)	(0.598)	(0.702)	**(0.041)**	(0.901)	(0.845)	(0.136)
AR+SVR-ANOVA	-1.425	-0.612	-0.422	-0.575	**-2.009**	-1.693	-0.934	-0.772	**-2.229**	-0.311	-0.714	-1.555
	(0.082)	(0.273)	(0.338)	(0.285)	**(0.027)**	(0.051)	(0.179)	(0.223)	**(0.017)**	(0.379)	(0.240)	(0.065)
AR+FFNN	-0.131	1.456	1.738	1.597	-1.401	-1.175	0.722	1.432	**-2.445**	1.761	1.143	-0.662
	(0.448)	(0.922)	(0.954)	(0.939)	(0.086)	(0.125)	(0.762)	(0.919)	**(0.010)**	(0.956)	(0.869)	(0.257)
AR+RNN	0.777	2.011	2.130	2.041	-0.480	-0.341	1.534	1.748	-0.779	2.130	1.510	0.259
	(0.778)	(0.973)	(0.979)	(0.975)	(0.317)	(0.368)	(0.932)	(0.955)	(0.221)	(0.979)	(0.929)	(0.601)
Ave. BM	-1.592	-1.082	-0.761	-0.921	**-2.337**	**-1.962**	-1.180	-1.097	**-2.272**	-0.634	-1.081	**-1.756**
	(0.061)	(0.144)	(0.226)	(0.182)	**(0.013)**	**(0.030)**	(0.124)	(0.141)	**(0.015)**	(0.265)	(0.144)	**(0.045)**
Ave. Linear	-1.444	-0.232	-0.066	-0.265	**-2.142**	**-1.808**	-0.871	-0.628	**-2.281**	0.033	-0.520	-1.590
	(0.080)	(0.409)	(0.474)	(0.396)	**(0.020)**	**(0.041)**	(0.195)	(0.267)	**(0.015)**	(0.513)	(0.303)	(0.061)
Ave. Local	0.511	1.629	1.848	1.770	**-2.887**	**-2.163**	1.427	1.558	-1.314	1.820	1.857	-0.110
	(0.694)	(0.943)	(0.963)	(0.956)	**(0.004)**	**(0.019)**	(0.918)	(0.935)	(0.100)	(0.960)	(0.963)	(0.457)
Ave. Non-linear	-1.454	1.065	1.694	1.442	**-2.159**	**-1.818**	0.051	1.350	**-3.113**	1.433	0.703	-1.663
	(0.078)	(0.852)	(0.950)	(0.920)	**(0.020)**	**(0.040)**	(0.520)	(0.906)	**(0.002)**	(0.919)	(0.756)	(0.053)
Ave. AR+	-1.303	0.861	1.285	0.948	**-1.935**	-1.626	-0.204	0.120	**-2.887**	1.213	0.229	-1.469
	(0.101)	(0.802)	(0.896)	(0.825)	**(0.031)**	(0.057)	(0.420)	(0.547)	**(0.004)**	(0.883)	(0.590)	(0.076)
Tot. Ave.	**-1.852**	0.176	0.662	0.110	**-2.403**	**-2.013**	-0.848	-0.869	**-2.812**	0.497	-0.552	**-1.876**
	(0.037)	(0.569)	(0.743)	(0.544)	**(0.011)**	**(0.027)**	(0.202)	(0.196)	**(0.004)**	(0.688)	(0.292)	**(0.035)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.36: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 2$. $N = 30$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	**-1.808**	**-2.102**	-0.834	0.273	-1.276	-1.624	0.573	0.031	**-2.019**	-1.017	-0.576	-0.256
	(0.040)	**(0.022)**	(0.206)	(0.607)	(0.106)	(0.058)	(0.714)	(0.512)	**(0.026)**	(0.159)	(0.285)	(0.400)
RW	-1.586	-0.517	-0.288	1.234	-0.564	-1.445	1.540	0.597	-0.836	-0.126	0.021	0.327
	(0.062)	(0.304)	(0.388)	(0.886)	(0.289)	(0.080)	(0.933)	(0.723)	(0.205)	(0.450)	(0.508)	(0.627)
DDD	-0.922	-0.010	0.162	1.427	-0.106	-0.888	1.677	1.029	-0.391	0.308	0.486	0.736
	(0.182)	(0.496)	(0.564)	(0.918)	(0.458)	(0.191)	(0.948)	(0.844)	(0.349)	(0.620)	(0.685)	(0.766)
AR(p)	**-2.852**	**-2.278**	-1.292	0.314	-1.652	**-2.084**	0.756	-0.148	**-1.799**	-1.488	-1.313	-1.141
	(0.004)	**(0.015)**	(0.103)	(0.622)	(0.055)	**(0.023)**	(0.772)	(0.442)	**(0.041)**	(0.074)	(0.100)	(0.132)
GETS	**-2.477**	**-2.264**	-1.534	0.079	-1.698	**-2.101**	0.486	-0.453	**-1.881**	-1.547	-1.477	-1.411
	(0.010)	**(0.016)**	(0.068)	(0.531)	(0.050)	**(0.022)**	(0.685)	(0.327)	**(0.035)**	(0.066)	(0.075)	(0.084)
GETS-IIS	**-2.546**	-1.502	-1.155	0.352	-1.410	**-2.136**	0.630	-0.062	-1.466	-0.932	-0.934	-0.356
	(0.008)	(0.072)	(0.129)	(0.636)	(0.085)	**(0.021)**	(0.733)	(0.476)	(0.077)	(0.179)	(0.179)	(0.362)
GETS-SIS	-1.317	-0.764	-0.652	0.531	-0.718	-1.263	0.819	0.255	-1.080	-0.366	-0.245	0.032
	(0.099)	(0.226)	(0.260)	(0.700)	(0.239)	(0.108)	(0.790)	(0.600)	(0.145)	(0.359)	(0.404)	(0.512)
GETS-DDD	-0.041	0.629	0.770	1.788	0.457	-0.045	2.268	1.778	0.196	0.849	0.983	1.288
	(0.484)	(0.733)	(0.776)	(0.958)	(0.675)	(0.482)	(0.985)	(0.957)	(0.577)	(0.799)	(0.833)	(0.896)
GETS-IIS-DDD	0.304	0.866	0.986	1.894	0.665	0.200	2.333	1.938	0.432	1.048	1.166	1.467
	(0.618)	(0.803)	(0.834)	(0.966)	(0.744)	(0.578)	(0.987)	(0.969)	(0.665)	(0.848)	(0.873)	(0.923)
GETS-SIS-DDD	-0.192	0.542	0.686	1.776	0.372	-0.146	2.365	1.789	0.102	0.780	0.912	1.246
	(0.425)	(0.704)	(0.751)	(0.957)	(0.644)	(0.442)	(0.988)	(0.958)	(0.540)	(0.779)	(0.815)	(0.889)
Ridge, CV	-0.958	0.552	0.440	1.324	0.113	-0.780	1.500	1.316	-0.552	1.426	1.214	1.692
	(0.173)	(0.707)	(0.669)	(0.902)	(0.545)	(0.221)	(0.928)	(0.901)	(0.292)	(0.918)	(0.883)	(0.949)
Lasso, CV	-0.900	0.747	0.492	1.432	0.157	-0.759	1.603	1.466	-0.504	1.540	1.334	1.905
	(0.188)	(0.769)	(0.687)	(0.919)	(0.562)	(0.227)	(0.940)	(0.923)	(0.309)	(0.933)	(0.904)	(0.967)
ELNET, CV	-0.935	0.690	0.469	1.425	0.131	-0.777	1.592	1.444	-0.511	1.454	1.303	1.852
	(0.179)	(0.752)	(0.679)	(0.918)	(0.552)	(0.222)	(0.939)	(0.920)	(0.306)	(0.922)	(0.899)	(0.963)
Ridge, AIC	**-2.914**	**-1.738**	-1.028	0.612	-1.456	**-2.011**	1.082	0.232	-1.629	-1.065	-0.861	-0.176
	(0.003)	**(0.046)**	(0.156)	(0.727)	(0.078)	**(0.027)**	(0.856)	(0.591)	(0.057)	(0.148)	(0.198)	(0.431)
Lasso, AIC	**-2.928**	**-2.430**	-1.136	0.422	**-1.738**	**-2.130**	0.761	0.066	**-1.848**	-1.694	-1.285	-0.662
	(0.003)	**(0.011)**	(0.133)	(0.662)	**(0.046)**	**(0.021)**	(0.774)	(0.526)	**(0.037)**	(0.050)	(0.104)	(0.257)
ELNET, AIC	**-2.759**	**-2.214**	-1.000	0.575	-1.597	**-2.041**	0.921	0.265	**-1.770**	-1.442	-0.948	-0.110
	(0.005)	**(0.017)**	(0.163)	(0.715)	(0.061)	**(0.025)**	(0.818)	(0.604)	**(0.044)**	(0.080)	(0.175)	(0.456)
k-NN	0.489	1.627	1.575	2.009	1.401	0.480	2.337	2.142	2.887	2.159	1.935	2.403
	(0.686)	(0.943)	(0.937)	(0.973)	(0.914)	(0.683)	(0.987)	(0.980)	(0.996)	(0.980)	(0.969)	(0.989)
wk-NN	0.359	1.342	1.346	1.693	1.175	0.341	1.962	1.808	2.163	1.818	1.626	2.013
	(0.639)	(0.905)	(0.906)	(0.949)	(0.875)	(0.632)	(0.970)	(0.959)	(0.981)	(0.960)	(0.943)	(0.973)
RF	-1.680	-0.975	-0.250	0.934	-0.722	-1.534	1.180	0.871	-1.427	-0.051	0.204	0.848
	(0.052)	(0.169)	(0.402)	(0.821)	(0.238)	(0.068)	(0.876)	(0.805)	(0.082)	(0.480)	(0.580)	(0.798)
FFNN	**-3.046**	**-2.364**	-0.535	0.772	-1.432	**-1.748**	1.097	0.628	-1.558	-1.350	-0.120	0.869
	(0.002)	**(0.013)**	(0.298)	(0.777)	(0.081)	**(0.045)**	(0.859)	(0.733)	(0.065)	(0.094)	(0.453)	(0.804)
RNN	1.048	2.213	1.802	2.229	2.445	0.779	2.272	2.281	1.314	3.113	2.887	2.812
	(0.848)	(0.983)	(0.959)	(0.983)	(0.990)	(0.779)	(0.985)	(0.985)	(0.900)	(0.998)	(0.996)	(0.996)
SVR-LIN	**-2.766**	**-1.824**	-1.318	0.311	**-1.761**	**-2.130**	0.634	-0.033	**-1.820**	-1.433	-1.213	-0.497
	(0.005)	**(0.039)**	(0.099)	(0.621)	**(0.044)**	**(0.021)**	(0.735)	(0.487)	**(0.040)**	(0.081)	(0.117)	(0.312)
SVR-POLY	-1.674	-1.493	-1.035	0.714	-1.143	-1.510	1.081	0.520	**-1.857**	-0.703	-0.229	0.552
	(0.052)	(0.073)	(0.155)	(0.760)	(0.131)	(0.071)	(0.856)	(0.697)	**(0.037)**	(0.244)	(0.410)	(0.708)
SVR-RBF	-0.243	1.127	1.121	1.555	0.662	-0.259	1.756	1.590	0.110	1.663	1.469	1.876
	(0.405)	(0.865)	(0.864)	(0.935)	(0.743)	(0.399)	(0.955)	(0.939)	(0.543)	(0.947)	(0.924)	(0.965)
SVR-ANOVA	-	1.519	1.024	3.057	1.627	-0.023	2.206	2.089	0.303	1.745	2.878	2.141
	-	(0.930)	(0.843)	(0.998)	(0.943)	(0.491)	(0.982)	(0.977)	(0.618)	(0.954)	(0.996)	(0.980)
AR+SVR-POLY	-1.519	-	0.315	1.543	-0.258	-1.066	1.688	1.507	-0.771	1.680	1.557	2.321
	(0.070)	-	(0.623)	(0.933)	(0.399)	(0.148)	(0.949)	(0.929)	(0.223)	(0.948)	(0.935)	(0.986)
AR+SVR-RBF	-1.024	-0.315	-	1.146	-0.390	-0.985	1.354	1.029	-0.819	0.284	0.506	1.023
	(0.157)	(0.377)	-	(0.869)	(0.350)	(0.167)	(0.907)	(0.844)	(0.210)	(0.611)	(0.692)	(0.843)
AR+SVR-ANOVA	**-3.057**	-1.543	-1.146	-	-1.328	**-2.015**	0.549	-0.432	-1.433	-0.955	-0.960	-0.589
	(0.002)	(0.067)	(0.131)	-	(0.097)	**(0.027)**	(0.706)	(0.335)	(0.081)	(0.174)	(0.172)	(0.280)
AR+FFNN	-1.627	0.258	0.390	1.328	-	-1.330	1.352	1.098	-0.509	1.366	1.731	1.423
	(0.057)	(0.601)	(0.650)	(0.903)	-	(0.097)	(0.907)	(0.859)	(0.307)	(0.909)	(0.953)	(0.917)
AR+RNN	0.023	1.066	0.985	2.015	1.330	-	1.935	1.626	0.319	1.698	2.058	1.806
	(0.509)	(0.852)	(0.833)	(0.973)	(0.903)	-	(0.969)	(0.943)	(0.624)	(0.950)	(0.976)	(0.959)
Ave. BM	**-2.206**	-1.688	-1.354	-0.549	-1.352	**-1.935**	-	-1.515	**-1.769**	-1.138	-1.035	-0.992
	(0.018)	(0.051)	(0.093)	(0.294)	(0.093)	**(0.031)**	-	(0.070)	**(0.044)**	(0.132)	(0.155)	(0.165)
Ave. Linear	**-2.089**	-1.507	-1.029	0.432	-1.098	-1.626	1.515	-	-1.562	-0.805	-0.602	-0.348
	(0.023)	(0.071)	(0.156)	(0.665)	(0.141)	(0.057)	(0.930)	-	(0.065)	(0.214)	(0.276)	(0.365)
Ave. Local	-0.303	0.771	0.819	1.433	0.509	-0.319	1.769	1.562	-	1.444	1.243	1.845
	(0.382)	(0.777)	(0.790)	(0.919)	(0.693)	(0.376)	(0.956)	(0.935)	-	(0.920)	(0.888)	(0.962)
Ave. Non-linear	**-1.745**	-1.680	-0.284	0.955	-1.366	-1.698	1.138	0.805	-1.444	-	0.565	1.294
	(0.046)	(0.052)	(0.389)	(0.826)	(0.091)	(0.050)	(0.868)	(0.786)	(0.080)	-	(0.712)	(0.897)
Ave. AR+	**-2.878**	-1.557	-0.506	0.960	**-1.731**	**-2.058**	1.035	0.602	-1.243	-0.565	-	0.720
	(0.004)	(0.065)	(0.308)	(0.828)	**(0.047)**	**(0.024)**	(0.845)	(0.724)	(0.112)	(0.288)	-	(0.761)
Tot. Ave.	**-2.141**	**-2.321**	-1.023	0.589	-1.423	**-1.806**	0.992	0.348	**-1.845**	-1.294	-0.720	-
	(0.020)	**(0.014)**	(0.157)	(0.720)	(0.083)	**(0.041)**	(0.835)	(0.635)	**(0.038)**	(0.103)	(0.239)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.37: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 3$. $N = 29$.

	AR(1)	RW	DDD	AR(p)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.198	-0.192	-0.897	-0.568	-0.972	-1.286	-0.660	-1.073	-0.668	-1.249	-1.317
	-	(0.422)	(0.425)	(0.189)	(0.287)	(0.170)	(0.104)	(0.257)	(0.146)	(0.255)	(0.111)	(0.099)
RW	0.198	-	0.086	-0.056	0.044	-0.263	**-2.345**	-1.421	**-1.906**	**-1.808**	-0.136	-0.160
	(0.578)	-	(0.534)	(0.478)	(0.517)	(0.397)	**(0.013)**	(0.083)	**(0.033)**	**(0.041)**	(0.447)	(0.437)
DDD	0.192	-0.086	-	-0.062	0.038	-0.270	**-2.354**	-1.499	**-1.962**	**-1.864**	-0.141	-0.166
	(0.575)	(0.466)	-	(0.475)	(0.515)	(0.394)	**(0.013)**	(0.073)	**(0.030)**	**(0.036)**	(0.444)	(0.435)
AR(p)	0.897	0.056	0.062	-	1.619	-0.981	-1.017	-0.457	-0.948	-0.463	-0.552	-0.750
	(0.811)	(0.522)	(0.525)	-	(0.942)	(0.167)	(0.159)	(0.326)	(0.176)	(0.323)	(0.293)	(0.230)
GETS	0.568	-0.044	-0.038	-1.619	-	-1.342	-1.087	-0.529	-0.986	-0.538	-1.366	-1.594
	(0.713)	(0.483)	(0.485)	(0.058)	-	(0.095)	(0.143)	(0.301)	(0.166)	(0.297)	(0.091)	(0.061)
GETS-IIS	0.972	0.263	0.270	0.981	1.342	-	-0.732	-0.233	-0.720	-0.237	0.485	0.402
	(0.830)	(0.603)	(0.606)	(0.833)	(0.905)	-	(0.235)	(0.409)	(0.239)	(0.407)	(0.684)	(0.655)
GETS-SIS	1.286	2.345	2.354	1.017	1.087	0.732	-	0.917	0.044	0.874	0.879	0.854
	(0.896)	(0.987)	(0.987)	(0.841)	(0.857)	(0.765)	-	(0.817)	(0.518)	(0.805)	(0.807)	(0.800)
GETS-DDD	0.660	1.421	1.499	0.457	0.529	0.233	-0.917	-	**-2.167**	-0.003	0.349	0.327
	(0.743)	(0.917)	(0.927)	(0.674)	(0.699)	(0.591)	(0.183)	-	**(0.019)**	(0.499)	(0.635)	(0.627)
GETS-IIS-DDD	1.073	1.906	1.962	0.948	0.986	0.720	-0.044	2.167	-	1.757	0.806	0.786
	(0.854)	(0.967)	(0.970)	(0.824)	(0.834)	(0.761)	(0.482)	(0.981)	-	(0.955)	(0.786)	(0.781)
GETS-SIS-DDD	0.668	1.808	1.864	0.463	0.538	0.237	-0.874	0.003	**-1.757**	-	0.357	0.334
	(0.745)	(0.959)	(0.964)	(0.677)	(0.703)	(0.593)	(0.195)	(0.501)	**(0.045)**	-	(0.638)	(0.630)
Ridge, CV	1.249	0.136	0.141	0.552	1.366	-0.485	-0.879	-0.349	-0.806	-0.357	-	-0.956
	(0.889)	(0.553)	(0.556)	(0.707)	(0.909)	(0.316)	(0.193)	(0.365)	(0.214)	(0.362)	-	(0.174)
Lasso, CV	1.317	0.160	0.166	0.750	1.594	-0.402	-0.854	-0.327	-0.786	-0.334	0.956	-
	(0.901)	(0.563)	(0.565)	(0.770)	(0.939)	(0.345)	(0.200)	(0.373)	(0.219)	(0.370)	(0.826)	-
ELNET, CV	1.237	0.149	0.154	0.697	1.573	-0.463	-0.871	-0.342	-0.807	-0.350	0.516	-0.642
	(0.887)	(0.559)	(0.561)	(0.754)	(0.937)	(0.323)	(0.196)	(0.367)	(0.213)	(0.364)	(0.695)	(0.263)
Ridge, AIC	0.691	-0.012	-0.006	-1.060	0.300	-1.255	-1.040	-0.499	-0.959	-0.507	-1.390	-1.608
	(0.752)	(0.495)	(0.498)	(0.149)	(0.617)	(0.110)	(0.154)	(0.311)	(0.173)	(0.308)	(0.088)	(0.059)
Lasso, AIC	0.712	-0.040	-0.035	-0.905	0.020	-1.164	-1.066	-0.513	-0.960	-0.522	**-1.959**	**-2.466**
	(0.759)	(0.484)	(0.486)	(0.187)	(0.508)	(0.127)	(0.148)	(0.306)	(0.173)	(0.303)	**(0.030)**	**(0.010)**
ELNET, AIC	0.727	-0.039	-0.033	-0.891	0.045	-1.151	-1.074	-0.515	-0.963	-0.523	**-1.725**	**-1.980**
	(0.763)	(0.484)	(0.487)	(0.190)	(0.518)	(0.130)	(0.146)	(0.305)	(0.172)	(0.303)	**(0.048)**	**(0.029)**
k-NN	2.907	1.541	1.547	2.447	2.415	1.940	0.880	1.192	0.764	1.154	2.216	2.181
	(0.996)	(0.933)	(0.934)	(0.990)	(0.989)	(0.969)	(0.807)	(0.878)	(0.774)	(0.871)	(0.983)	(0.981)
wk-NN	2.561	1.406	1.412	2.134	2.127	1.690	0.762	1.070	0.653	1.034	1.928	1.897
	(0.992)	(0.915)	(0.916)	(0.979)	(0.979)	(0.949)	(0.774)	(0.853)	(0.740)	(0.845)	(0.968)	(0.966)
RF	0.295	-0.107	-0.102	-0.558	-0.196	-1.116	-1.219	-0.640	-1.137	-0.649	-0.760	-0.861
	(0.615)	(0.458)	(0.460)	(0.291)	(0.423)	(0.137)	(0.117)	(0.264)	(0.133)	(0.261)	(0.227)	(0.198)
FFNN	0.931	0.039	0.045	-0.110	0.589	-0.815	-0.991	-0.454	-0.929	-0.465	-1.546	**-2.212**
	(0.820)	(0.515)	(0.518)	(0.456)	(0.720)	(0.211)	(0.165)	(0.327)	(0.181)	(0.323)	(0.067)	**(0.018)**
RNN	1.591	0.823	0.844	1.346	1.427	1.104	-0.050	0.421	-0.020	0.404	1.140	1.124
	(0.939)	(0.791)	(0.797)	(0.905)	(0.918)	(0.860)	(0.480)	(0.661)	(0.492)	(0.655)	(0.868)	(0.865)
SVR-LIN	0.942	0.286	0.291	0.864	1.184	0.293	-0.640	-0.181	-0.645	-0.185	0.639	0.560
	(0.823)	(0.611)	(0.613)	(0.803)	(0.877)	(0.614)	(0.264)	(0.429)	(0.262)	(0.427)	(0.736)	(0.710)
SVR-POLY	0.980	0.863	0.867	0.977	1.027	0.954	0.240	0.628	0.360	0.643	0.927	0.915
	(0.832)	(0.802)	(0.803)	(0.831)	(0.843)	(0.826)	(0.594)	(0.732)	(0.639)	(0.737)	(0.819)	(0.816)
SVR-RBF	2.325	0.608	0.616	1.046	1.281	0.445	-0.650	0.025	-0.442	0.025	0.895	0.839
	(0.986)	(0.726)	(0.729)	(0.848)	(0.895)	(0.670)	(0.260)	(0.510)	(0.331)	(0.510)	(0.811)	(0.796)
SVR-ANOVA	1.521	1.383	1.397	1.670	1.732	1.679	0.396	1.202	0.807	1.201	1.454	1.445
	(0.930)	(0.911)	(0.913)	(0.947)	(0.953)	(0.948)	(0.652)	(0.880)	(0.787)	(0.880)	(0.921)	(0.920)
AR+SVR-POLY	1.203	0.832	0.838	1.256	1.351	1.297	-0.027	0.442	-0.002	0.453	1.155	1.136
	(0.881)	(0.794)	(0.796)	(0.890)	(0.906)	(0.897)	(0.489)	(0.669)	(0.499)	(0.673)	(0.871)	(0.867)
AR+SVR-RBF	2.432	0.823	0.842	1.992	2.089	1.393	-0.191	0.327	-0.142	0.322	1.604	1.606
	(0.989)	(0.791)	(0.796)	(0.972)	(0.977)	(0.913)	(0.425)	(0.627)	(0.444)	(0.625)	(0.940)	(0.940)
AR+SVR-ANOVA	1.278	0.701	0.709	0.923	1.071	0.568	-0.373	0.167	-0.285	0.167	0.796	0.741
	(0.894)	(0.756)	(0.758)	(0.818)	(0.853)	(0.713)	(0.356)	(0.566)	(0.389)	(0.566)	(0.784)	(0.768)
AR+FFNN	1.641	0.677	0.680	1.511	1.684	1.286	-0.155	0.269	-0.139	0.276	1.632	1.614
	(0.944)	(0.748)	(0.749)	(0.929)	(0.948)	(0.895)	(0.439)	(0.605)	(0.445)	(0.608)	(0.943)	(0.941)
AR+RNN	1.704	1.355	1.353	1.789	1.822	1.828	0.605	1.038	0.774	1.058	1.772	1.760
	(0.950)	(0.907)	(0.907)	(0.958)	(0.960)	(0.961)	(0.725)	(0.846)	(0.777)	(0.850)	(0.956)	(0.955)
Ave. BM	-1.114	-1.257	-1.254	-1.311	-1.181	-1.312	**-3.443**	-1.641	**-1.862**	-1.628	-1.316	-1.335
	(0.137)	(0.110)	(0.110)	(0.100)	(0.124)	(0.100)	**(0.001)**	(0.056)	**(0.037)**	(0.057)	(0.099)	(0.096)
Ave. Linear	-0.862	-0.656	-0.648	-1.396	-1.131	-1.297	**-2.067**	-1.109	-1.474	-1.110	-1.339	-1.366
	(0.198)	(0.259)	(0.261)	(0.087)	(0.134)	(0.103)	**(0.024)**	(0.138)	(0.076)	(0.138)	(0.096)	(0.091)
Ave. Local	2.633	0.873	0.880	1.793	1.836	1.143	-0.074	0.427	-0.031	0.419	1.534	1.491
	(0.993)	(0.805)	(0.807)	(0.958)	(0.962)	(0.869)	(0.471)	(0.664)	(0.488)	(0.661)	(0.932)	(0.926)
Ave. Non-linear	1.105	0.297	0.303	1.200	1.685	0.678	-0.681	-0.196	-0.709	-0.201	0.785	0.708
	(0.861)	(0.616)	(0.618)	(0.880)	(0.948)	(0.748)	(0.251)	(0.423)	(0.242)	(0.421)	(0.780)	(0.758)
Ave. AR+	1.672	0.699	0.705	1.903	2.063	1.990	-0.243	0.226	-0.236	0.230	1.865	1.834
	(0.947)	(0.755)	(0.757)	(0.966)	(0.976)	(0.972)	(0.405)	(0.589)	(0.408)	(0.590)	(0.964)	(0.961)
Tot. Ave.	0.359	-0.134	-0.128	-1.443	-0.658	-1.171	-1.244	-0.619	-1.062	-0.625	-1.291	-1.366
	(0.639)	(0.447)	(0.449)	(0.080)	(0.258)	(0.126)	(0.112)	(0.270)	(0.149)	(0.269)	(0.104)	(0.091)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.38: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 3$. $N = 29$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	-1.237	-0.691	-0.712	-0.727	**-2.907**	**-2.561**	-0.295	-0.931	-1.591	-0.942	-0.980	**-2.325**
	(0.113)	(0.248)	(0.241)	(0.237)	**(0.004)**	**(0.008)**	(0.385)	(0.180)	(0.061)	(0.177)	(0.168)	**(0.014)**
RW	-0.149	0.012	0.040	0.039	-1.541	-1.406	0.107	-0.039	-0.823	-0.286	-0.863	-0.608
	(0.441)	(0.505)	(0.516)	(0.516)	(0.067)	(0.085)	(0.542)	(0.485)	(0.209)	(0.389)	(0.198)	(0.274)
DDD	-0.154	0.006	0.035	0.033	-1.547	-1.412	0.102	-0.045	-0.844	-0.291	-0.867	-0.616
	(0.439)	(0.502)	(0.514)	(0.513)	(0.066)	(0.084)	(0.540)	(0.482)	(0.203)	(0.387)	(0.197)	(0.271)
AR(p)	-0.697	1.060	0.905	0.891	**-2.447**	**-2.134**	0.558	0.110	-1.346	-0.864	-0.977	-1.046
	(0.246)	(0.851)	(0.813)	(0.810)	**(0.010)**	**(0.021)**	(0.709)	(0.544)	(0.095)	(0.197)	(0.169)	(0.152)
GETS	-1.573	-0.300	-0.020	-0.045	**-2.415**	**-2.127**	0.196	-0.589	-1.427	-1.184	-1.027	-1.281
	(0.063)	(0.383)	(0.492)	(0.482)	**(0.011)**	**(0.021)**	(0.577)	(0.280)	(0.082)	(0.123)	(0.157)	(0.105)
GETS-IIS	0.463	1.255	1.164	1.151	**-1.940**	-1.690	1.116	0.815	-1.104	-0.293	-0.954	-0.445
	(0.677)	(0.890)	(0.873)	(0.870)	**(0.031)**	(0.051)	(0.863)	(0.789)	(0.140)	(0.386)	(0.174)	(0.330)
GETS-SIS	0.871	1.040	1.066	1.074	-0.880	-0.762	1.219	0.991	0.050	0.640	-0.240	0.650
	(0.804)	(0.846)	(0.852)	(0.854)	(0.193)	(0.226)	(0.883)	(0.835)	(0.520)	(0.736)	(0.406)	(0.740)
GETS-DDD	0.342	0.499	0.513	0.515	-1.192	-1.070	0.640	0.454	-0.421	0.181	-0.628	-0.025
	(0.633)	(0.689)	(0.694)	(0.695)	(0.122)	(0.147)	(0.736)	(0.673)	(0.339)	(0.571)	(0.268)	(0.490)
GETS-IIS-DDD	0.807	0.959	0.960	0.963	-0.764	-0.653	1.137	0.929	0.020	0.645	-0.360	0.442
	(0.787)	(0.827)	(0.827)	(0.828)	(0.226)	(0.260)	(0.867)	(0.819)	(0.508)	(0.738)	(0.361)	(0.669)
GETS-SIS-DDD	0.350	0.507	0.522	0.523	-1.154	-1.034	0.649	0.465	-0.404	0.185	-0.643	-0.025
	(0.636)	(0.692)	(0.697)	(0.697)	(0.129)	(0.155)	(0.739)	(0.677)	(0.345)	(0.573)	(0.263)	(0.490)
Ridge, CV	-0.516	1.390	1.959	1.725	**-2.216**	**-1.928**	0.760	1.546	-1.140	-0.639	-0.927	-0.895
	(0.305)	(0.912)	(0.970)	(0.952)	**(0.017)**	**(0.032)**	(0.773)	(0.933)	(0.132)	(0.264)	(0.181)	(0.189)
Lasso, CV	0.642	1.608	2.466	1.980	**-2.181**	**-1.897**	0.861	2.212	-1.124	-0.560	-0.915	-0.839
	(0.737)	(0.941)	(0.990)	(0.971)	**(0.019)**	**(0.034)**	(0.802)	(0.982)	(0.135)	(0.290)	(0.184)	(0.204)
ELNET, CV	-	1.672	2.147	1.803	**-2.179**	**-1.896**	0.815	2.111	-1.134	-0.621	-0.928	-0.858
	-	(0.947)	(0.980)	(0.959)	**(0.019)**	**(0.034)**	(0.789)	(0.978)	(0.133)	(0.270)	(0.181)	(0.199)
Ridge, AIC	-1.672	-	0.422	0.453	**-2.439**	**-2.133**	0.300	-0.445	-1.387	-1.152	-1.018	-1.166
	(0.053)	-	(0.662)	(0.673)	**(0.011)**	**(0.021)**	(0.617)	(0.330)	(0.088)	(0.130)	(0.159)	(0.127)
Lasso, AIC	**-2.147**	-0.422	-	-0.065	**-2.496**	**-2.190**	0.206	-0.763	-1.440	-1.125	-1.007	-1.334
	(0.020)	(0.338)	-	(0.474)	**(0.009)**	**(0.019)**	(0.581)	(0.226)	(0.081)	(0.135)	(0.161)	(0.096)
ELNET, AIC	**-1.803**	-0.453	0.065	-	**-2.508**	**-2.198**	0.204	-0.659	-1.439	-1.089	-1.002	-1.337
	(0.041)	(0.327)	(0.526)	-	**(0.009)**	**(0.018)**	(0.580)	(0.258)	(0.081)	(0.143)	(0.162)	(0.096)
k-NN	2.179	2.439	2.496	2.508	-	1.749	2.560	2.375	1.641	1.752	0.240	2.048
	(0.981)	(0.989)	(0.991)	(0.991)	-	(0.954)	(0.992)	(0.988)	(0.944)	(0.955)	(0.594)	(0.975)
wk-NN	1.896	2.133	2.190	2.198	**-1.749**	-	2.261	2.073	1.334	1.522	0.172	1.799
	(0.966)	(0.979)	(0.981)	(0.982)	**(0.046)**	-	(0.984)	(0.976)	(0.903)	(0.930)	(0.568)	(0.959)
RF	-0.815	-0.300	-0.206	-0.204	**-2.560**	**-2.261**	-	-0.485	-1.624	-0.952	-1.034	-1.387
	(0.211)	(0.383)	(0.419)	(0.420)	**(0.008)**	**(0.016)**	-	(0.316)	(0.058)	(0.175)	(0.155)	(0.088)
FFNN	**-2.111**	0.445	0.763	0.659	**-2.375**	**-2.073**	0.485	-	-1.268	-0.941	-0.986	-1.099
	(0.022)	(0.670)	(0.774)	(0.742)	**(0.012)**	**(0.024)**	(0.684)	-	(0.108)	(0.177)	(0.166)	(0.141)
RNN	1.134	1.387	1.440	1.439	-1.641	-1.334	1.624	1.268	-	0.931	-0.349	0.535
	(0.867)	(0.912)	(0.919)	(0.919)	(0.056)	(0.097)	(0.942)	(0.892)	-	(0.820)	(0.365)	(0.702)
SVR-LIN	0.621	1.152	1.125	1.089	**-1.752**	-1.522	0.952	0.941	-0.931	-	-0.976	-0.342
	(0.730)	(0.870)	(0.865)	(0.857)	**(0.045)**	(0.070)	(0.825)	(0.823)	(0.180)	-	(0.169)	(0.368)
SVR-POLY	0.928	1.018	1.007	1.002	-0.240	-0.172	1.034	0.986	0.349	0.976	-	0.550
	(0.819)	(0.841)	(0.839)	(0.838)	(0.406)	(0.432)	(0.845)	(0.834)	(0.635)	(0.831)	-	(0.707)
SVR-RBF	0.858	1.166	1.334	1.337	**-2.048**	**-1.799**	1.387	1.099	-0.535	0.342	-0.550	-
	(0.801)	(0.873)	(0.904)	(0.904)	**(0.025)**	**(0.041)**	(0.912)	(0.859)	(0.298)	(0.632)	(0.293)	-
SVR-ANOVA	1.472	1.688	1.648	1.636	-0.350	-0.250	1.773	1.601	0.621	1.518	-0.001	0.920
	(0.924)	(0.949)	(0.945)	(0.943)	(0.364)	(0.402)	(0.956)	(0.940)	(0.730)	(0.930)	(0.500)	(0.817)
AR+SVR-POLY	1.163	1.334	1.310	1.295	-0.768	-0.639	1.356	1.273	0.023	1.383	-0.691	0.445
	(0.873)	(0.904)	(0.900)	(0.897)	(0.225)	(0.264)	(0.907)	(0.893)	(0.509)	(0.911)	(0.248)	(0.670)
AR+SVR-RBF	1.602	1.962	2.169	2.113	**-2.143**	**-1.763**	3.424	1.846	-0.249	1.089	-0.429	0.706
	(0.940)	(0.970)	(0.981)	(0.978)	**(0.020)**	**(0.044)**	(0.999)	(0.962)	(0.402)	(0.857)	(0.336)	(0.757)
AR+SVR-ANOVA	0.768	1.072	1.031	1.071	-1.322	-1.150	0.941	0.875	-0.318	0.481	-0.483	0.218
	(0.775)	(0.854)	(0.844)	(0.853)	(0.098)	(0.130)	(0.823)	(0.805)	(0.376)	(0.683)	(0.317)	(0.585)
AR+FFNN	1.620	1.679	1.786	1.736	-1.154	-0.966	1.538	1.788	-0.176	1.675	-0.554	0.404
	(0.942)	(0.948)	(0.958)	(0.953)	(0.129)	(0.171)	(0.932)	(0.958)	(0.431)	(0.947)	(0.292)	(0.655)
AR+RNN	1.778	1.836	1.819	1.810	0.122	0.187	1.828	1.856	0.907	1.998	0.718	1.108
	(0.957)	(0.962)	(0.960)	(0.959)	(0.548)	(0.573)	(0.961)	(0.963)	(0.814)	(0.972)	(0.761)	(0.861)
Ave. BM	-1.326	-1.210	-1.156	-1.179	**-2.988**	**-2.790**	-1.132	-1.204	**-1.856**	-1.202	-1.140	**-2.845**
	(0.098)	(0.118)	(0.129)	(0.124)	**(0.003)**	**(0.005)**	(0.134)	(0.119)	**(0.037)**	(0.120)	(0.132)	**(0.004)**
Ave. Linear	-1.356	-1.196	-1.084	-1.133	**-2.944**	**-2.678**	-0.903	-1.168	**-1.768**	-1.161	-1.092	**-3.022**
	(0.093)	(0.121)	(0.144)	(0.133)	**(0.003)**	**(0.006)**	(0.187)	(0.126)	**(0.044)**	(0.128)	(0.142)	**(0.003)**
Ave. Local	1.488	1.822	1.967	1.965	**-3.029**	**-2.353**	2.095	1.759	-0.024	0.958	-0.303	0.985
	(0.926)	(0.960)	(0.970)	(0.970)	**(0.003)**	**(0.013)**	(0.977)	(0.955)	(0.490)	(0.827)	(0.382)	(0.834)
Ave. Non-linear	0.790	1.736	1.519	1.442	**-1.845**	-1.598	1.142	1.190	-1.075	0.011	-0.928	-0.377
	(0.782)	(0.953)	(0.930)	(0.920)	**(0.038)**	(0.061)	(0.869)	(0.878)	(0.146)	(0.504)	(0.181)	(0.354)
Ave. AR+	1.891	2.107	2.065	2.024	-1.322	-1.112	1.840	2.089	-0.324	3.966	-0.669	0.318
	(0.966)	(0.978)	(0.976)	(0.974)	(0.098)	(0.138)	(0.962)	(0.977)	(0.374)	(1.000)	(0.254)	(0.624)
Tot. Ave.	-1.319	-1.100	-0.636	-0.768	**-2.709**	**-2.389**	-0.103	-0.808	-1.609	-1.021	-1.004	**-1.802**
	(0.099)	(0.140)	(0.265)	(0.224)	**(0.006)**	**(0.012)**	(0.459)	(0.213)	(0.059)	(0.158)	(0.162)	**(0.041)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.39: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 3$. $N = 29$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.521	-1.203	**-2.432**	-1.278	-1.641	**-1.704**	1.114	0.862	**-2.633**	-1.105	-1.672	-0.359
	(0.070)	(0.119)	**(0.011)**	(0.106)	(0.056)	**(0.050)**	(0.863)	(0.802)	**(0.007)**	(0.139)	(0.053)	(0.361)
RW	-1.383	-0.832	-0.823	-0.701	-0.677	-1.355	1.257	0.656	-0.873	-0.297	-0.699	0.134
	(0.089)	(0.206)	(0.209)	(0.244)	(0.252)	(0.093)	(0.890)	(0.741)	(0.195)	(0.384)	(0.245)	(0.553)
DDD	-1.397	-0.838	-0.842	-0.709	-0.680	-1.353	1.254	0.648	-0.880	-0.303	-0.705	0.128
	(0.087)	(0.204)	(0.204)	(0.242)	(0.251)	(0.093)	(0.890)	(0.739)	(0.193)	(0.382)	(0.243)	(0.551)
AR(p)	-1.670	-1.256	**-1.992**	-0.923	-1.511	**-1.789**	1.311	1.396	**-1.793**	-1.200	**-1.903**	1.443
	(0.053)	(0.110)	**(0.028)**	(0.182)	(0.071)	**(0.042)**	(0.900)	(0.913)	**(0.042)**	(0.120)	**(0.034)**	(0.920)
GETS	**-1.732**	-1.351	**-2.089**	-1.071	-1.684	**-1.822**	1.181	1.131	**-1.836**	-1.685	**-2.063**	0.658
	(0.047)	(0.094)	**(0.023)**	(0.147)	(0.052)	**(0.040)**	(0.876)	(0.866)	**(0.038)**	(0.052)	**(0.024)**	(0.742)
GETS-IIS	-1.679	-1.297	-1.393	-0.568	-1.286	**-1.828**	1.312	1.297	-1.143	-0.678	**-1.990**	1.171
	(0.052)	(0.103)	(0.087)	(0.287)	(0.105)	**(0.039)**	(0.900)	(0.897)	(0.131)	(0.252)	**(0.028)**	(0.874)
GETS-SIS	-0.396	0.027	0.191	0.373	0.155	-0.605	3.443	2.067	0.074	0.681	0.243	1.244
	(0.348)	(0.511)	(0.575)	(0.644)	(0.561)	(0.275)	(0.999)	(0.976)	(0.529)	(0.749)	(0.595)	(0.888)
GETS-DDD	-1.202	-0.442	-0.327	-0.167	-0.269	-1.038	1.641	1.109	-0.427	0.196	-0.226	0.619
	(0.120)	(0.331)	(0.373)	(0.434)	(0.395)	(0.154)	(0.944)	(0.862)	(0.336)	(0.577)	(0.411)	(0.730)
GETS-IIS-DDD	-0.807	0.002	0.142	0.285	0.139	-0.774	1.862	1.474	0.031	0.709	0.236	1.062
	(0.213)	(0.501)	(0.556)	(0.611)	(0.555)	(0.223)	(0.963)	(0.924)	(0.512)	(0.758)	(0.592)	(0.851)
GETS-SIS-DDD	-1.201	-0.453	-0.322	-0.167	-0.276	-1.058	1.628	1.110	-0.419	0.201	-0.230	0.625
	(0.120)	(0.327)	(0.375)	(0.434)	(0.392)	(0.150)	(0.943)	(0.862)	(0.339)	(0.579)	(0.410)	(0.731)
Ridge, CV	-1.454	-1.155	-1.604	-0.796	-1.632	**-1.772**	1.316	1.339	-1.534	-0.785	**-1.865**	1.291
	(0.079)	(0.129)	(0.060)	(0.216)	(0.057)	**(0.044)**	(0.901)	(0.904)	(0.068)	(0.220)	**(0.036)**	(0.896)
Lasso, CV	-1.445	-1.136	-1.606	-0.741	-1.614	**-1.760**	1.335	1.366	-1.491	-0.708	**-1.834**	1.366
	(0.080)	(0.133)	(0.060)	(0.232)	(0.059)	**(0.045)**	(0.904)	(0.909)	(0.074)	(0.242)	**(0.039)**	(0.909)
ELNET, CV	-1.472	-1.163	-1.602	-0.768	-1.620	**-1.778**	1.326	1.356	-1.488	-0.790	**-1.891**	1.319
	(0.076)	(0.127)	(0.060)	(0.225)	(0.058)	**(0.043)**	(0.902)	(0.907)	(0.074)	(0.218)	**(0.034)**	(0.901)
Ridge, AIC	-1.688	-1.334	**-1.962**	-1.072	-1.679	**-1.836**	1.210	1.196	**-1.822**	**-1.736**	**-2.107**	1.100
	(0.051)	(0.096)	**(0.030)**	(0.146)	(0.052)	**(0.038)**	(0.882)	(0.879)	**(0.040)**	**(0.047)**	**(0.022)**	(0.860)
Lasso, AIC	-1.648	-1.310	**-2.169**	-1.031	**-1.786**	**-1.819**	1.156	1.084	**-1.967**	-1.519	**-2.065**	0.636
	(0.055)	(0.100)	**(0.019)**	(0.156)	**(0.042)**	**(0.040)**	(0.871)	(0.856)	**(0.030)**	(0.070)	**(0.024)**	(0.735)
ELNET, AIC	-1.636	-1.295	**-2.113**	-1.071	**-1.736**	**-1.810**	1.179	1.133	**-1.965**	-1.442	**-2.024**	0.768
	(0.057)	(0.103)	**(0.022)**	(0.147)	**(0.047)**	**(0.041)**	(0.876)	(0.867)	**(0.030)**	(0.080)	**(0.026)**	(0.776)
k-NN	0.350	0.768	2.143	1.322	1.154	-0.122	2.988	2.944	3.029	1.845	1.322	2.709
	(0.636)	(0.775)	(0.980)	(0.902)	(0.871)	(0.452)	(0.997)	(0.997)	(0.997)	(0.962)	(0.902)	(0.994)
wk-NN	0.250	0.639	1.763	1.150	0.966	-0.187	2.790	2.678	2.353	1.598	1.112	2.389
	(0.598)	(0.736)	(0.956)	(0.870)	(0.829)	(0.427)	(0.995)	(0.994)	(0.987)	(0.939)	(0.862)	(0.988)
RF	**-1.773**	-1.356	**-3.424**	-0.941	-1.538	**-1.828**	1.132	0.903	**-2.095**	-1.142	**-1.840**	0.103
	(0.044)	(0.093)	**(0.001)**	(0.177)	(0.068)	**(0.039)**	(0.866)	(0.813)	**(0.023)**	(0.131)	**(0.038)**	(0.541)
FFNN	-1.601	-1.273	**-1.846**	-0.875	**-1.788**	**-1.856**	1.204	1.168	**-1.759**	-1.190	**-2.089**	0.808
	(0.060)	(0.107)	**(0.038)**	(0.195)	**(0.042)**	**(0.037)**	(0.881)	(0.874)	**(0.045)**	(0.122)	**(0.023)**	(0.787)
RNN	-0.621	-0.023	0.249	0.318	0.176	-0.907	1.856	1.768	0.024	1.075	0.324	1.609
	(0.270)	(0.491)	(0.598)	(0.624)	(0.569)	(0.186)	(0.963)	(0.956)	(0.510)	(0.854)	(0.626)	(0.941)
SVR-LIN	-1.518	-1.383	-1.089	-0.481	-1.675	**-1.998**	1.202	1.161	-0.958	-0.011	**-3.966**	1.021
	(0.070)	(0.089)	(0.143)	(0.317)	(0.053)	**(0.028)**	(0.880)	(0.872)	(0.173)	(0.496)	**(0.000)**	(0.842)
SVR-POLY	0.001	0.691	0.429	0.483	0.554	-0.718	1.140	1.092	0.303	0.928	0.669	1.004
	(0.500)	(0.752)	(0.664)	(0.683)	(0.708)	(0.239)	(0.868)	(0.858)	(0.618)	(0.819)	(0.746)	(0.838)
SVR-RBF	-0.920	-0.445	-0.706	-0.218	-0.404	-1.108	2.845	3.022	-0.985	0.377	-0.318	1.802
	(0.183)	(0.330)	(0.243)	(0.415)	(0.345)	(0.139)	(0.996)	(0.997)	(0.166)	(0.646)	(0.376)	(0.959)
SVR-ANOVA	-	0.935	0.798	0.708	0.741	-0.712	1.809	1.795	0.467	1.587	1.034	1.647
	-	(0.821)	(0.784)	(0.758)	(0.768)	(0.241)	(0.959)	(0.958)	(0.678)	(0.938)	(0.845)	(0.945)
AR+SVR-POLY	-0.935	-	0.187	0.290	0.303	**-2.848**	1.363	1.351	0.032	1.246	0.608	1.271
	(0.179)	-	(0.573)	(0.613)	(0.618)	**(0.004)**	(0.908)	(0.906)	(0.513)	(0.888)	(0.726)	(0.893)
AR+SVR-RBF	-0.798	-0.187	-	0.192	0.018	-1.009	2.232	2.375	-0.487	1.372	0.177	2.518
	(0.216)	(0.427)	-	(0.575)	(0.507)	(0.161)	(0.983)	(0.988)	(0.315)	(0.909)	(0.569)	(0.991)
AR+SVR-ANOVA	-0.708	-0.290	-0.192	-	-0.164	-1.018	2.169	1.964	-0.346	0.496	-0.085	1.290
	(0.242)	(0.387)	(0.425)	-	(0.435)	(0.159)	(0.981)	(0.970)	(0.366)	(0.688)	(0.466)	(0.896)
AR+FFNN	-0.741	-0.303	-0.018	0.164	-	-1.674	1.454	1.494	-0.179	1.495	0.351	1.560
	(0.232)	(0.382)	(0.493)	(0.565)	-	(0.053)	(0.921)	(0.927)	(0.430)	(0.927)	(0.636)	(0.935)
AR+RNN	0.712	2.848	1.009	1.018	1.674	-	1.670	1.692	0.828	1.931	1.729	1.739
	(0.759)	(0.996)	(0.839)	(0.841)	(0.947)	-	(0.947)	(0.949)	(0.793)	(0.968)	(0.953)	(0.953)
Ave. BM	**-1.809**	-1.363	**-2.232**	**-2.169**	-1.454	-1.670	-	-1.304	**-2.422**	-1.304	-1.566	-1.248
	(0.041)	(0.092)	**(0.017)**	**(0.019)**	(0.079)	(0.053)	-	(0.101)	**(0.011)**	(0.101)	(0.064)	(0.111)
Ave. Linear	**-1.795**	-1.351	**-2.375**	**-1.964**	-1.494	-1.692	1.304	-	**-2.482**	-1.324	-1.649	-1.246
	(0.042)	(0.094)	**(0.012)**	**(0.030)**	(0.073)	(0.051)	(0.899)	-	**(0.010)**	(0.098)	(0.055)	(0.112)
Ave. Local	-0.467	-0.032	0.487	0.346	0.179	-0.828	2.422	2.482	-	1.045	0.320	2.239
	(0.322)	(0.487)	(0.685)	(0.634)	(0.570)	(0.207)	(0.989)	(0.990)	-	(0.848)	(0.624)	(0.983)
Ave. Non-linear	-1.587	-1.246	-1.372	-0.496	-1.495	**-1.931**	1.304	1.324	-1.045	-	**-3.579**	1.255
	(0.062)	(0.112)	(0.091)	(0.312)	(0.073)	**(0.032)**	(0.899)	(0.902)	(0.152)	-	**(0.001)**	(0.890)
Ave. AR+	-1.034	-0.608	-0.177	0.085	-0.351	**-1.729**	1.566	1.649	-0.320	3.579	-	1.809
	(0.155)	(0.274)	(0.431)	(0.534)	(0.364)	**(0.047)**	(0.936)	(0.945)	(0.376)	(0.999)	-	(0.959)
Tot. Ave.	-1.647	-1.271	**-2.518**	-1.290	-1.560	**-1.739**	1.248	1.246	**-2.239**	-1.255	**-1.809**	-
	(0.055)	(0.107)	**(0.009)**	(0.104)	(0.065)	**(0.047)**	(0.889)	(0.888)	**(0.017)**	(0.110)	**(0.041)**	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.40: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 4$. $N = 28$.

	AR(1)	RW	DDD	AR(p)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-1.003	-0.835	1.013	-0.857	-0.627	**-2.762**	-1.012	-1.096	-1.061	1.489	0.985
	-	(0.162)	(0.205)	(0.840)	(0.199)	(0.268)	**(0.005)**	(0.160)	(0.141)	(0.149)	(0.926)	(0.833)
RW	1.003	-	1.343	1.012	0.889	0.965	-1.309	-0.398	-0.794	-0.682	1.349	1.310
	(0.838)	-	(0.905)	(0.840)	(0.809)	(0.829)	(0.101)	(0.347)	(0.217)	(0.250)	(0.906)	(0.899)
DDD	0.835	-1.343	-	0.849	0.668	0.715	-1.669	-1.014	-1.072	-1.036	1.225	1.153
	(0.795)	(0.095)	-	(0.798)	(0.745)	(0.760)	(0.053)	(0.160)	(0.147)	(0.155)	(0.884)	(0.871)
AR(p)	-1.013	-1.012	-0.849	-	-0.882	-0.655	**-2.768**	-1.016	-1.097	-1.063	1.448	0.820
	(0.160)	(0.160)	(0.202)	-	(0.193)	(0.259)	**(0.005)**	(0.159)	(0.141)	(0.149)	(0.920)	(0.790)
GETS	0.857	-0.889	-0.668	0.882	-	0.047	**-2.944**	-0.941	-1.073	-1.022	1.345	1.341
	(0.801)	(0.191)	(0.255)	(0.807)	-	(0.518)	**(0.003)**	(0.178)	(0.146)	(0.158)	(0.905)	(0.905)
GETS-IIS	0.627	-0.965	-0.715	0.655	-0.047	-	**-3.081**	-1.028	-1.176	-1.115	1.184	1.202
	(0.732)	(0.171)	(0.240)	(0.741)	(0.482)	-	**(0.002)**	(0.157)	(0.125)	(0.137)	(0.877)	(0.880)
GETS-SIS	2.762	1.309	1.669	2.768	2.944	3.081	-	1.186	0.841	0.919	3.254	3.331
	(0.995)	(0.899)	(0.947)	(0.995)	(0.997)	(0.998)	-	(0.877)	(0.796)	(0.817)	(0.998)	(0.999)
GETS-DDD	1.012	0.398	1.014	1.016	0.941	1.028	-1.186	-	-1.150	-1.044	1.299	1.282
	(0.840)	(0.653)	(0.840)	(0.841)	(0.822)	(0.843)	(0.123)	-	(0.130)	(0.153)	(0.898)	(0.895)
GETS-IIS-DDD	1.096	0.794	1.072	1.097	1.073	1.176	-0.841	1.150	-	1.252	1.332	1.333
	(0.859)	(0.783)	(0.853)	(0.859)	(0.854)	(0.875)	(0.204)	(0.870)	-	(0.889)	(0.903)	(0.903)
GETS-SIS-DDD	1.061	0.682	1.036	1.063	1.022	1.115	-0.919	1.044	-1.252	-	1.305	1.299
	(0.851)	(0.750)	(0.845)	(0.851)	(0.842)	(0.863)	(0.183)	(0.847)	(0.111)	-	(0.899)	(0.897)
Ridge, CV	-1.489	-1.349	-1.225	-1.448	-1.345	-1.184	**-3.254**	-1.299	-1.332	-1.305	-	-1.113
	(0.074)	(0.094)	(0.116)	(0.080)	(0.095)	(0.123)	**(0.002)**	(0.102)	(0.097)	(0.101)	-	(0.138)
Lasso, CV	-0.985	-1.310	-1.153	-0.820	-1.341	-1.202	**-3.331**	-1.282	-1.333	-1.299	1.113	-
	(0.167)	(0.101)	(0.129)	(0.210)	(0.095)	(0.120)	**(0.001)**	(0.105)	(0.097)	(0.103)	(0.862)	-
ELNET, CV	-1.001	-1.317	-1.161	-0.840	-1.347	-1.212	**-3.344**	-1.288	-1.337	-1.304	1.085	-1.395
	(0.163)	(0.099)	(0.128)	(0.204)	(0.095)	(0.118)	**(0.001)**	(0.104)	(0.096)	(0.102)	(0.856)	(0.087)
Ridge, AIC	1.220	-0.802	-0.585	1.226	1.062	0.569	**-2.990**	-0.854	-0.992	-0.940	1.657	1.823
	(0.883)	(0.215)	(0.282)	(0.885)	(0.851)	(0.713)	**(0.003)**	(0.200)	(0.165)	(0.178)	(0.945)	(0.960)
Lasso, AIC	0.673	-0.978	-0.763	0.719	-0.643	-0.539	**-3.220**	-1.025	-1.148	-1.097	1.397	1.505
	(0.747)	(0.168)	(0.226)	(0.761)	(0.263)	(0.297)	**(0.002)**	(0.157)	(0.130)	(0.141)	(0.913)	(0.928)
ELNET, AIC	0.564	-1.012	-0.798	0.618	-0.814	-0.834	**-3.342**	-1.059	-1.178	-1.127	1.336	1.424
	(0.711)	(0.160)	(0.216)	(0.729)	(0.211)	(0.206)	**(0.001)**	(0.150)	(0.124)	(0.135)	(0.904)	(0.917)
k-NN	1.044	-0.150	-0.006	1.096	0.649	0.598	-1.211	-0.193	-0.309	-0.280	1.522	1.225
	(0.847)	(0.441)	(0.498)	(0.859)	(0.739)	(0.723)	(0.118)	(0.424)	(0.380)	(0.391)	(0.930)	(0.884)
wk-NN	1.219	-0.027	0.125	1.267	0.836	0.773	-1.009	-0.076	-0.199	-0.169	1.657	1.385
	(0.883)	(0.489)	(0.549)	(0.892)	(0.795)	(0.777)	(0.161)	(0.470)	(0.422)	(0.434)	(0.945)	(0.911)
RF	-0.344	-1.462	-1.252	-0.263	-1.241	**-1.810**	**-3.528**	-1.501	-1.577	-1.524	0.491	0.170
	(0.367)	(0.078)	(0.111)	(0.397)	(0.113)	**(0.041)**	**(0.001)**	(0.073)	(0.063)	(0.070)	(0.686)	(0.567)
FFNN	0.345	-1.136	-0.907	0.394	-0.406	-1.598	**-3.329**	-1.224	-1.349	-1.291	1.068	1.070
	(0.634)	(0.133)	(0.186)	(0.652)	(0.344)	(0.061)	**(0.001)**	(0.116)	(0.094)	(0.104)	(0.853)	(0.853)
RNN	1.794	1.363	1.433	1.788	1.831	1.901	0.870	1.433	1.404	1.410	1.809	1.845
	(0.958)	(0.908)	(0.918)	(0.958)	(0.961)	(0.966)	(0.804)	(0.918)	(0.914)	(0.915)	(0.959)	(0.962)
SVR-LIN	0.989	-0.892	-0.692	0.956	-0.355	-0.421	**-2.930**	-0.924	-1.044	-0.999	1.368	1.410
	(0.834)	(0.190)	(0.247)	(0.826)	(0.363)	(0.339)	**(0.003)**	(0.182)	(0.153)	(0.163)	(0.909)	(0.915)
SVR-POLY	0.948	0.128	0.319	0.948	0.960	1.056	-0.940	0.055	-0.221	-0.140	1.102	1.106
	(0.824)	(0.551)	(0.624)	(0.824)	(0.827)	(0.850)	(0.178)	(0.522)	(0.413)	(0.445)	(0.860)	(0.861)
SVR-RBF	0.688	-0.789	-0.628	0.788	-0.015	-0.004	**-2.098**	-0.848	-0.981	-0.926	1.750	1.178
	(0.751)	(0.218)	(0.267)	(0.781)	(0.494)	(0.499)	**(0.023)**	(0.202)	(0.168)	(0.181)	(0.954)	(0.875)
SVR-ANOVA	0.847	-0.393	-0.137	0.862	0.611	0.865	-1.424	-0.576	-0.853	-0.767	1.187	1.166
	(0.798)	(0.349)	(0.446)	(0.802)	(0.727)	(0.803)	(0.083)	(0.285)	(0.201)	(0.225)	(0.877)	(0.873)
AR+SVR-POLY	1.319	-0.571	-0.407	1.537	0.264	0.218	**-2.190**	-0.595	-0.701	-0.670	1.962	1.363
	(0.901)	(0.287)	(0.343)	(0.932)	(0.603)	(0.585)	**(0.019)**	(0.278)	(0.245)	(0.254)	(0.970)	(0.908)
AR+SVR-RBF	2.113	0.386	0.638	2.165	1.564	1.538	-0.628	0.299	0.100	0.149	2.750	2.421
	(0.978)	(0.649)	(0.736)	(0.980)	(0.935)	(0.932)	(0.268)	(0.617)	(0.539)	(0.558)	(0.995)	(0.989)
AR+SVR-ANOVA	1.289	0.208	0.351	1.327	1.015	0.992	-0.682	0.148	0.016	0.048	1.634	1.435
	(0.896)	(0.582)	(0.636)	(0.902)	(0.840)	(0.835)	(0.251)	(0.558)	(0.506)	(0.519)	(0.943)	(0.919)
AR+FFNN	0.985	-0.815	-0.622	1.083	-0.143	-0.090	**-2.914**	-0.833	-0.942	-0.901	1.743	1.640
	(0.833)	(0.211)	(0.270)	(0.856)	(0.444)	(0.464)	**(0.004)**	(0.206)	(0.177)	(0.188)	(0.954)	(0.944)
AR+RNN	1.199	-0.712	-0.507	1.273	0.370	0.355	**-2.616**	-0.730	-0.845	-0.802	2.942	3.025
	(0.880)	(0.241)	(0.308)	(0.893)	(0.643)	(0.637)	**(0.007)**	(0.236)	(0.203)	(0.215)	(0.997)	(0.997)
Ave. BM	-0.831	-1.648	-1.555	-0.778	-1.076	-1.043	**-3.534**	-1.515	-1.500	-1.479	-0.140	-0.646
	(0.207)	(0.055)	(0.066)	(0.222)	(0.146)	(0.153)	**(0.001)**	(0.071)	(0.073)	(0.075)	(0.445)	(0.262)
Ave. Linear	-0.613	-1.386	-1.248	-0.535	-1.011	-0.933	**-3.685**	-1.323	-1.356	-1.326	0.834	-0.085
	(0.273)	(0.089)	(0.111)	(0.299)	(0.161)	(0.180)	**(0.001)**	(0.098)	(0.093)	(0.098)	(0.794)	(0.466)
Ave. Local	0.624	-0.587	-0.438	0.703	0.074	0.073	**-2.168**	-0.614	-0.714	-0.686	1.410	0.975
	(0.731)	(0.281)	(0.332)	(0.756)	(0.529)	(0.529)	**(0.020)**	(0.272)	(0.241)	(0.249)	(0.915)	(0.831)
Ave. Non-linear	1.293	-0.541	-0.315	1.288	0.982	1.258	**-2.093**	-0.637	-0.821	-0.762	1.537	1.631
	(0.896)	(0.296)	(0.378)	(0.896)	(0.833)	(0.890)	**(0.023)**	(0.265)	(0.209)	(0.226)	(0.932)	(0.943)
Ave. AR+	2.879	-0.716	-0.543	3.986	0.022	0.031	**-2.547**	-0.740	-0.848	-0.811	2.334	1.864
	(0.996)	(0.240)	(0.296)	(1.000)	(0.509)	(0.512)	**(0.008)**	(0.233)	(0.202)	(0.212)	(0.986)	(0.963)
Tot. Ave.	-0.619	-1.106	-0.948	-0.432	-1.053	-0.852	**-3.226**	-1.100	-1.173	-1.139	1.801	1.081
	(0.271)	(0.139)	(0.176)	(0.334)	(0.151)	(0.201)	**(0.002)**	(0.140)	(0.125)	(0.132)	(0.959)	(0.855)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.41: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 4$. $N = 28$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	1.001	-1.220	-0.673	-0.564	-1.044	-1.219	0.344	-0.345	**-1.794**	-0.989	-0.948	-0.688
	(0.837)	(0.117)	(0.253)	(0.289)	(0.153)	(0.117)	(0.633)	(0.366)	**(0.042)**	(0.166)	(0.176)	(0.249)
RW	1.317	0.802	0.978	1.012	0.150	0.027	1.462	1.136	-1.363	0.892	-0.128	0.789
	(0.901)	(0.785)	(0.832)	(0.840)	(0.559)	(0.511)	(0.922)	(0.867)	(0.092)	(0.810)	(0.449)	(0.782)
DDD	1.161	0.585	0.763	0.798	0.006	-0.125	1.252	0.907	-1.433	0.692	-0.319	0.628
	(0.872)	(0.718)	(0.774)	(0.784)	(0.502)	(0.451)	(0.889)	(0.814)	(0.082)	(0.753)	(0.376)	(0.733)
AR(p)	0.840	-1.226	-0.719	-0.618	-1.096	-1.267	0.263	-0.394	**-1.788**	-0.956	-0.948	-0.788
	(0.796)	(0.115)	(0.239)	(0.271)	(0.141)	(0.108)	(0.603)	(0.348)	**(0.042)**	(0.174)	(0.176)	(0.219)
GETS	1.347	-1.062	0.643	0.814	-0.649	-0.836	1.241	0.406	**-1.831**	0.355	-0.960	0.015
	(0.905)	(0.149)	(0.737)	(0.789)	(0.261)	(0.205)	(0.887)	(0.656)	**(0.039)**	(0.637)	(0.173)	(0.506)
GETS-IIS	1.212	-0.569	0.539	0.834	-0.598	-0.773	1.810	1.598	**-1.901**	0.421	-1.056	0.004
	(0.882)	(0.287)	(0.703)	(0.794)	(0.277)	(0.223)	(0.959)	(0.939)	**(0.034)**	(0.661)	(0.150)	(0.501)
GETS-SIS	3.344	2.990	3.220	3.342	1.211	1.009	3.528	3.329	-0.870	2.930	0.940	2.098
	(0.999)	(0.997)	(0.998)	(0.999)	(0.882)	(0.839)	(0.999)	(0.999)	(0.196)	(0.997)	(0.822)	(0.977)
GETS-DDD	1.288	0.854	1.025	1.059	0.193	0.076	1.501	1.224	-1.433	0.924	-0.055	0.848
	(0.896)	(0.800)	(0.843)	(0.850)	(0.576)	(0.530)	(0.927)	(0.884)	(0.082)	(0.818)	(0.478)	(0.798)
GETS-IIS-DDD	1.337	0.992	1.148	1.178	0.309	0.199	1.577	1.349	-1.404	1.044	0.221	0.981
	(0.904)	(0.835)	(0.870)	(0.876)	(0.620)	(0.578)	(0.937)	(0.906)	(0.086)	(0.847)	(0.587)	(0.832)
GETS-SIS-DDD	1.304	0.940	1.097	1.127	0.280	0.169	1.524	1.291	-1.410	0.999	0.140	0.926
	(0.898)	(0.822)	(0.859)	(0.865)	(0.609)	(0.566)	(0.930)	(0.896)	(0.085)	(0.837)	(0.555)	(0.819)
Ridge, CV	-1.085	-1.657	-1.397	-1.336	-1.522	-1.657	-0.491	-1.068	**-1.809**	-1.368	-1.102	**-1.750**
	(0.144)	(0.055)	(0.087)	(0.096)	(0.070)	(0.055)	(0.314)	(0.147)	**(0.041)**	(0.091)	(0.140)	**(0.046)**
Lasso, CV	1.395	**-1.823**	-1.505	-1.424	-1.225	-1.385	-0.170	-1.070	**-1.845**	-1.410	-1.106	-1.178
	(0.913)	**(0.040)**	(0.072)	(0.083)	(0.116)	(0.089)	(0.433)	(0.147)	**(0.038)**	(0.085)	(0.139)	(0.125)
ELNET, CV	-	**-1.825**	-1.514	-1.435	-1.235	-1.393	-0.193	-1.085	**-1.845**	-1.415	-1.109	-1.195
	-	**(0.040)**	(0.071)	(0.081)	(0.114)	(0.087)	(0.424)	(0.144)	**(0.038)**	(0.084)	(0.139)	(0.121)
Ridge, AIC	1.825	-	1.725	1.580	-0.577	-0.770	1.477	0.713	**-1.776**	0.650	-0.873	0.161
	(0.960)	-	(0.952)	(0.937)	(0.284)	(0.224)	(0.924)	(0.759)	**(0.043)**	(0.740)	(0.195)	(0.563)
Lasso, AIC	1.514	**-1.725**	-	1.743	-0.710	-0.891	1.310	0.201	**-1.834**	0.109	-0.997	-0.112
	(0.929)	**(0.048)**	-	(0.954)	(0.242)	(0.190)	(0.899)	(0.579)	**(0.039)**	(0.543)	(0.164)	(0.456)
ELNET, AIC	1.435	-1.580	**-1.743**	-	-0.737	-0.920	1.301	0.077	**-1.839**	0.002	-1.024	-0.157
	(0.919)	(0.063)	**(0.046)**	-	(0.234)	(0.183)	(0.898)	(0.530)	**(0.038)**	(0.501)	(0.157)	(0.438)
k-NN	1.235	0.577	0.710	0.737	-	-1.391	1.006	0.698	-1.167	0.758	-0.221	0.673
	(0.886)	(0.716)	(0.758)	(0.766)	-	(0.088)	(0.838)	(0.754)	(0.127)	(0.773)	(0.414)	(0.747)
wk-NN	1.393	0.770	0.891	0.920	1.391	-	1.164	0.874	-1.086	0.943	-0.104	0.824
	(0.913)	(0.776)	(0.810)	(0.817)	(0.912)	-	(0.873)	(0.805)	(0.143)	(0.823)	(0.459)	(0.791)
RF	0.193	-1.477	-1.310	-1.301	-1.006	-1.164	-	**-2.492**	**-1.947**	-0.945	-1.328	-0.664
	(0.576)	(0.076)	(0.101)	(0.102)	(0.162)	(0.127)	-	**(0.010)**	**(0.031)**	(0.176)	(0.098)	(0.256)
FFNN	1.085	-0.713	-0.201	-0.077	-0.698	-0.874	2.492	-	**-1.913**	-0.066	-1.159	-0.170
	(0.856)	(0.241)	(0.421)	(0.470)	(0.246)	(0.195)	(0.990)	-	**(0.033)**	(0.474)	(0.128)	(0.433)
RNN	1.845	1.776	1.834	1.839	1.167	1.086	1.947	1.913	-	1.840	2.093	1.784
	(0.962)	(0.957)	(0.961)	(0.962)	(0.873)	(0.857)	(0.969)	(0.967)	-	(0.962)	(0.977)	(0.957)
SVR-LIN	1.415	-0.650	-0.109	-0.002	-0.758	-0.943	0.945	0.066	**-1.840**	-	-0.956	-0.177
	(0.916)	(0.260)	(0.457)	(0.499)	(0.227)	(0.177)	(0.824)	(0.526)	**(0.038)**	-	(0.174)	(0.430)
SVR-POLY	1.109	0.873	0.997	1.024	0.221	0.104	1.328	1.159	**-2.093**	0.956	-	0.714
	(0.861)	(0.805)	(0.836)	(0.843)	(0.586)	(0.541)	(0.902)	(0.872)	**(0.023)**	(0.826)	-	(0.759)
SVR-RBF	1.195	-0.161	0.112	0.157	-0.673	-0.824	0.664	0.170	**-1.784**	0.177	-0.714	-
	(0.879)	(0.437)	(0.544)	(0.562)	(0.253)	(0.209)	(0.744)	(0.567)	**(0.043)**	(0.570)	(0.241)	-
SVR-ANOVA	1.173	0.528	0.726	0.755	-0.081	-0.219	1.343	0.889	**-2.124**	0.877	-0.765	0.759
	(0.874)	(0.699)	(0.763)	(0.771)	(0.468)	(0.414)	(0.905)	(0.809)	**(0.021)**	(0.806)	(0.225)	(0.773)
AR+SVR-POLY	1.375	0.124	0.391	0.438	-0.707	-0.938	0.758	0.359	-1.547	0.517	-0.588	0.294
	(0.910)	(0.549)	(0.651)	(0.668)	(0.243)	(0.178)	(0.773)	(0.639)	(0.067)	(0.695)	(0.281)	(0.615)
AR+SVR-RBF	2.431	1.501	1.660	1.718	2.232	1.457	2.086	1.662	-0.996	1.805	0.218	1.650
	(0.989)	(0.928)	(0.946)	(0.951)	(0.983)	(0.922)	(0.977)	(0.946)	(0.164)	(0.959)	(0.586)	(0.945)
AR+SVR-ANOVA	1.443	1.016	1.103	1.117	0.460	0.287	1.226	1.042	-1.028	1.150	0.119	1.130
	(0.920)	(0.841)	(0.860)	(0.863)	(0.675)	(0.612)	(0.885)	(0.847)	(0.156)	(0.870)	(0.547)	(0.866)
AR+FFNN	1.651	-0.656	0.131	0.233	-0.714	-0.902	0.839	0.188	**-1.740**	0.371	-0.842	-0.068
	(0.945)	(0.259)	(0.552)	(0.591)	(0.241)	(0.187)	(0.796)	(0.574)	**(0.047)**	(0.643)	(0.204)	(0.473)
AR+RNN	3.078	0.186	0.627	0.709	-0.651	-0.911	1.796	0.692	-1.565	0.700	-0.691	0.265
	(0.998)	(0.573)	(0.732)	(0.758)	(0.260)	(0.185)	(0.958)	(0.753)	(0.065)	(0.755)	(0.248)	(0.604)
Ave. BM	-0.632	-1.274	-1.121	-1.090	-1.307	-1.455	-0.542	-1.021	**-1.766**	-0.959	-1.106	-1.292
	(0.266)	(0.107)	(0.136)	(0.143)	(0.101)	(0.079)	(0.296)	(0.158)	**(0.044)**	(0.173)	(0.139)	(0.104)
Ave. Linear	-0.049	-1.308	-1.064	-1.017	-1.195	-1.351	-0.174	-0.838	**-1.765**	-0.878	-1.049	-1.040
	(0.481)	(0.101)	(0.148)	(0.159)	(0.121)	(0.094)	(0.432)	(0.205)	**(0.044)**	(0.194)	(0.152)	(0.154)
Ave. Local	0.990	-0.047	0.181	0.223	-1.494	**-1.763**	0.662	0.215	-1.494	0.237	-0.633	0.082
	(0.835)	(0.482)	(0.571)	(0.587)	(0.073)	**(0.045)**	(0.743)	(0.584)	(0.073)	(0.593)	(0.266)	(0.533)
Ave. Non-linear	1.633	0.735	1.157	1.193	-0.269	-0.443	1.692	1.356	**-1.897**	1.498	-0.736	0.673
	(0.943)	(0.766)	(0.871)	(0.878)	(0.395)	(0.331)	(0.949)	(0.907)	**(0.034)**	(0.927)	(0.234)	(0.747)
Ave. AR+	1.875	-0.240	0.235	0.305	-0.771	-0.971	0.816	0.241	-1.672	0.451	-0.744	0.049
	(0.964)	(0.406)	(0.592)	(0.619)	(0.224)	(0.170)	(0.789)	(0.594)	(0.053)	(0.672)	(0.232)	(0.519)
Tot. Ave.	1.143	-1.514	-1.049	-0.948	-1.160	-1.327	0.145	-0.623	**-1.787**	-1.062	-1.002	-0.945
	(0.868)	(0.071)	(0.152)	(0.176)	(0.128)	(0.098)	(0.557)	(0.269)	**(0.043)**	(0.149)	(0.163)	(0.177)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.42: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Univariate. $h = 4$. $N = 28$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-0.847	-1.319	**-2.113**	-1.289	-0.985	-1.199	0.831	0.613	-0.624	-1.293	**-2.879**	0.619
	(0.202)	(0.099)	**(0.022)**	(0.104)	(0.167)	(0.120)	(0.793)	(0.727)	(0.269)	(0.104)	**(0.004)**	(0.729)
RW	0.393	0.571	-0.386	-0.208	0.815	0.712	1.648	1.386	0.587	0.541	0.716	1.106
	(0.651)	(0.713)	(0.351)	(0.418)	(0.789)	(0.759)	(0.945)	(0.911)	(0.719)	(0.704)	(0.760)	(0.861)
DDD	0.137	0.407	-0.638	-0.351	0.622	0.507	1.555	1.248	0.438	0.315	0.543	0.948
	(0.554)	(0.657)	(0.264)	(0.364)	(0.730)	(0.692)	(0.934)	(0.889)	(0.668)	(0.622)	(0.704)	(0.824)
AR(p)	-0.862	-1.537	**-2.265**	-1.327	-1.083	-1.273	0.778	0.535	-0.703	-1.288	**-3.986**	0.432
	(0.198)	(0.068)	**(0.020)**	(0.098)	(0.144)	(0.107)	(0.778)	(0.701)	(0.244)	(0.104)	**(0.000)**	(0.666)
GETS	-0.611	-0.264	-1.564	-1.015	0.143	-0.370	1.076	1.011	-0.074	-0.982	-0.022	1.053
	(0.273)	(0.397)	(0.065)	(0.160)	(0.556)	(0.357)	(0.854)	(0.839)	(0.471)	(0.167)	(0.491)	(0.849)
GETS-IIS	-0.865	-0.218	-1.538	-0.992	0.090	-0.355	1.043	0.933	-0.073	-1.258	-0.031	0.852
	(0.197)	(0.415)	(0.068)	(0.165)	(0.536)	(0.363)	(0.847)	(0.820)	(0.471)	(0.110)	(0.488)	(0.799)
GETS-SIS	1.424	2.190	0.628	0.682	2.914	2.616	3.534	3.685	2.168	2.093	2.547	3.226
	(0.917)	(0.981)	(0.732)	(0.749)	(0.996)	(0.993)	(0.999)	(0.999)	(0.980)	(0.977)	(0.992)	(0.998)
GETS-DDD	0.576	0.595	-0.299	-0.148	0.833	0.730	1.515	1.323	0.614	0.637	0.740	1.100
	(0.715)	(0.722)	(0.383)	(0.442)	(0.794)	(0.764)	(0.929)	(0.902)	(0.728)	(0.735)	(0.767)	(0.860)
GETS-IIS-DDD	0.853	0.701	-0.100	-0.016	0.942	0.845	1.500	1.356	0.714	0.821	0.848	1.173
	(0.799)	(0.755)	(0.461)	(0.494)	(0.823)	(0.797)	(0.927)	(0.907)	(0.759)	(0.791)	(0.798)	(0.875)
GETS-SIS-DDD	0.767	0.670	-0.149	-0.048	0.901	0.802	1.479	1.326	0.686	0.762	0.811	1.139
	(0.775)	(0.746)	(0.442)	(0.481)	(0.812)	(0.785)	(0.925)	(0.902)	(0.751)	(0.774)	(0.788)	(0.868)
Ridge, CV	-1.187	**-1.962**	**-2.750**	-1.634	**-1.743**	**-2.942**	0.140	-0.834	-1.410	-1.537	**-2.334**	**-1.801**
	(0.123)	**(0.030)**	**(0.005)**	(0.057)	**(0.046)**	**(0.003)**	(0.555)	(0.206)	(0.085)	(0.068)	**(0.014)**	**(0.041)**
Lasso, CV	-1.166	-1.363	**-2.421**	-1.435	-1.640	**-3.025**	0.646	0.085	-0.975	-1.631	**-1.864**	-1.081
	(0.127)	(0.092)	**(0.011)**	(0.081)	(0.056)	**(0.003)**	(0.738)	(0.534)	(0.169)	(0.057)	**(0.037)**	(0.145)
ELNET, CV	-1.173	-1.375	**-2.431**	-1.443	-1.651	**-3.078**	0.632	0.049	-0.990	-1.633	**-1.875**	-1.143
	(0.126)	(0.090)	**(0.011)**	(0.080)	(0.055)	**(0.002)**	(0.734)	(0.519)	(0.165)	(0.057)	**(0.036)**	(0.132)
Ridge, AIC	-0.528	-0.124	-1.501	-1.016	0.656	-0.186	1.274	1.308	0.047	-0.735	0.240	1.514
	(0.301)	(0.451)	(0.072)	(0.159)	(0.741)	(0.427)	(0.893)	(0.899)	(0.518)	(0.234)	(0.594)	(0.929)
Lasso, AIC	-0.726	-0.391	-1.660	-1.103	-0.131	-0.627	1.121	1.064	-0.181	-1.157	-0.235	1.049
	(0.237)	(0.349)	(0.054)	(0.140)	(0.448)	(0.268)	(0.864)	(0.852)	(0.429)	(0.129)	(0.408)	(0.848)
ELNET, AIC	-0.755	-0.438	**-1.718**	-1.117	-0.233	-0.709	1.090	1.017	-0.223	-1.193	-0.305	0.948
	(0.229)	(0.332)	**(0.049)**	(0.137)	(0.409)	(0.242)	(0.857)	(0.841)	(0.413)	(0.122)	(0.381)	(0.824)
k-NN	0.081	0.707	**-2.232**	-0.460	0.714	0.651	1.307	1.195	1.494	0.269	0.771	1.160
	(0.532)	(0.757)	**(0.017)**	(0.325)	(0.759)	(0.740)	(0.899)	(0.879)	(0.927)	(0.605)	(0.776)	(0.872)
wk-NN	0.219	0.938	-1.457	-0.287	0.902	0.911	1.455	1.351	1.763	0.443	0.971	1.327
	(0.586)	(0.822)	(0.078)	(0.388)	(0.813)	(0.815)	(0.921)	(0.906)	(0.955)	(0.669)	(0.830)	(0.902)
RF	-1.343	-0.758	**-2.086**	-1.226	-0.839	**-1.796**	0.542	0.174	-0.662	-1.692	-0.816	-0.145
	(0.095)	(0.227)	**(0.023)**	(0.115)	(0.204)	**(0.042)**	(0.704)	(0.568)	(0.257)	(0.051)	(0.211)	(0.443)
FFNN	-0.889	-0.359	-1.662	-1.042	-0.188	-0.692	1.021	0.838	-0.215	-1.356	-0.241	0.623
	(0.191)	(0.361)	(0.054)	(0.153)	(0.426)	(0.247)	(0.842)	(0.795)	(0.416)	(0.093)	(0.406)	(0.731)
RNN	2.124	1.547	0.996	1.028	1.740	1.565	1.766	1.765	1.494	1.897	1.672	1.787
	(0.979)	(0.933)	(0.836)	(0.844)	(0.953)	(0.935)	(0.956)	(0.956)	(0.927)	(0.966)	(0.947)	(0.957)
SVR-LIN	-0.877	-0.517	**-1.805**	-1.150	-0.371	-0.700	0.959	0.878	-0.237	-1.498	-0.451	1.062
	(0.194)	(0.305)	**(0.041)**	(0.130)	(0.357)	(0.245)	(0.827)	(0.806)	(0.407)	(0.073)	(0.328)	(0.851)
SVR-POLY	0.765	0.588	-0.218	-0.119	0.842	0.691	1.106	1.049	0.633	0.736	0.744	1.002
	(0.775)	(0.719)	(0.414)	(0.453)	(0.796)	(0.752)	(0.861)	(0.848)	(0.734)	(0.766)	(0.768)	(0.837)
SVR-RBF	-0.759	-0.294	-1.650	-1.130	0.068	-0.265	1.292	1.040	-0.082	-0.673	-0.049	0.945
	(0.227)	(0.385)	(0.055)	(0.134)	(0.527)	(0.396)	(0.896)	(0.846)	(0.467)	(0.253)	(0.481)	(0.823)
SVR-ANOVA	-	0.348	-0.695	-0.520	0.633	0.400	1.195	1.028	0.397	0.396	0.544	0.952
	-	(0.635)	(0.247)	(0.304)	(0.734)	(0.654)	(0.879)	(0.843)	(0.653)	(0.652)	(0.704)	(0.825)
AR+SVR-POLY	-0.348	-	**-1.718**	-1.075	0.457	-0.012	1.236	1.191	0.208	-0.301	0.604	1.427
	(0.365)	-	**(0.049)**	(0.146)	(0.674)	(0.495)	(0.886)	(0.878)	(0.581)	(0.383)	(0.724)	(0.918)
AR+SVR-RBF	0.695	1.718	-	0.078	1.616	1.874	2.652	2.391	3.161	1.095	1.781	2.295
	(0.753)	(0.951)	-	(0.531)	(0.941)	(0.964)	(0.993)	(0.988)	(0.998)	(0.858)	(0.957)	(0.985)
AR+SVR-ANOVA	0.520	1.075	-0.078	-	1.231	0.907	1.520	1.470	0.980	0.738	1.192	1.429
	(0.696)	(0.854)	(0.469)	-	(0.886)	(0.814)	(0.930)	(0.923)	(0.832)	(0.766)	(0.878)	(0.918)
AR+FFNN	-0.633	-0.457	-1.616	-1.231	-	-0.518	1.132	1.121	-0.143	-0.877	-0.251	1.503
	(0.266)	(0.326)	(0.059)	(0.114)	-	(0.304)	(0.866)	(0.864)	(0.444)	(0.194)	(0.402)	(0.928)
AR+RNN	-0.400	0.012	**-1.874**	-0.907	0.518	-	2.050	2.158	0.228	-0.328	0.365	2.029
	(0.346)	(0.505)	**(0.036)**	(0.186)	(0.696)	-	(0.975)	(0.980)	(0.589)	(0.373)	(0.641)	(0.974)
Ave. BM	-1.195	-1.236	**-2.652**	-1.520	-1.132	**-2.050**	-	-1.077	-1.031	-1.294	-1.215	-0.817
	(0.121)	(0.114)	**(0.007)**	(0.070)	(0.134)	**(0.025)**	-	(0.146)	(0.156)	(0.103)	(0.118)	(0.211)
Ave. Linear	-1.028	-1.191	**-2.391**	-1.470	-1.121	**-2.158**	1.077	-	-0.881	-1.246	-1.220	-0.543
	(0.157)	(0.122)	**(0.012)**	(0.077)	(0.136)	**(0.020)**	(0.854)	-	(0.193)	(0.112)	(0.117)	(0.296)
Ave. Local	-0.397	-0.208	**-3.161**	-0.980	0.143	-0.228	1.031	0.881	-	-0.352	0.085	0.832
	(0.347)	(0.419)	**(0.002)**	(0.168)	(0.556)	(0.411)	(0.844)	(0.807)	-	(0.364)	(0.533)	(0.794)
Ave. Non-linear	-0.396	0.301	-1.095	-0.738	0.877	0.328	1.294	1.246	0.352	-	0.667	1.346
	(0.348)	(0.617)	(0.142)	(0.234)	(0.806)	(0.627)	(0.897)	(0.888)	(0.636)	-	(0.745)	(0.905)
Ave. AR+	-0.544	-0.604	**-1.781**	-1.192	0.251	-0.365	1.215	1.220	-0.085	-0.667	-	2.185
	(0.296)	(0.276)	**(0.043)**	(0.122)	(0.598)	(0.359)	(0.882)	(0.883)	(0.467)	(0.255)	-	(0.981)
Tot. Ave.	-0.952	-1.427	**-2.295**	-1.429	-1.503	**-2.029**	0.817	0.543	-0.832	-1.346	**-2.185**	-
	(0.175)	(0.082)	**(0.015)**	(0.082)	(0.072)	**(0.026)**	(0.789)	(0.704)	(0.206)	(0.095)	**(0.019)**	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.43: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 0$. $N = 32$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-1.031	**-2.039**	-0.349	2.924	2.940	2.641	2.552	2.728	2.544	2.401	2.968
	-	(0.155)	**(0.025)**	(0.365)	(0.997)	(0.997)	(0.994)	(0.992)	(0.995)	(0.992)	(0.989)	(0.997)
RW	1.031	-	**-1.799**	0.171	3.370	3.374	3.264	3.179	3.187	3.176	2.762	3.359
	(0.845)	-	**(0.041)**	(0.567)	(0.999)	(0.999)	(0.999)	(0.998)	(0.998)	(0.998)	(0.995)	(0.999)
DDD	2.039	1.799	-	1.594	4.584	4.561	4.446	4.372	4.437	4.366	4.081	4.515
	(0.975)	(0.959)	-	(0.939)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
VAR(4)	0.349	-0.171	-1.594	-	2.648	2.658	2.328	2.271	2.495	2.260	2.424	2.691
	(0.635)	(0.433)	(0.061)	-	(0.994)	(0.994)	(0.987)	(0.985)	(0.991)	(0.984)	(0.989)	(0.994)
GETS	**-2.924**	**-3.370**	**-4.584**	**-2.648**	-	0.460	**-2.383**	**-2.808**	**-1.772**	**-2.774**	**-2.149**	-0.444
	(0.003)	**(0.001)**	**(0.000)**	**(0.006)**	-	(0.676)	**(0.012)**	**(0.004)**	**(0.043)**	**(0.005)**	**(0.020)**	(0.330)
GETS-IIS	**-2.940**	**-3.374**	**-4.561**	**-2.658**	-0.460	-	**-2.327**	**-2.751**	**-1.972**	**-2.720**	**-2.217**	-0.708
	(0.003)	**(0.001)**	**(0.000)**	**(0.006)**	(0.324)	-	**(0.013)**	**(0.005)**	**(0.029)**	**(0.005)**	**(0.017)**	(0.242)
GETS-SIS	**-2.641**	**-3.264**	**-4.446**	**-2.328**	2.383	2.327	-	-1.529	1.363	**-1.853**	-0.644	1.791
	(0.006)	**(0.001)**	**(0.000)**	**(0.013)**	(0.988)	(0.987)	-	(0.068)	(0.909)	**(0.037)**	(0.262)	(0.958)
GETS-DDD	**-2.552**	**-3.179**	**-4.372**	**-2.271**	2.808	2.751	1.529	-	1.885	-1.303	-0.476	2.130
	(0.008)	**(0.002)**	**(0.000)**	**(0.015)**	(0.996)	(0.995)	(0.932)	-	(0.966)	(0.101)	(0.319)	(0.979)
GETS-IIS-DDD	**-2.728**	**-3.187**	**-4.437**	**-2.495**	1.772	1.972	-1.363	**-1.885**	-	**-1.884**	-1.542	1.196
	(0.005)	**(0.002)**	**(0.000)**	**(0.009)**	(0.957)	(0.971)	(0.091)	**(0.034)**	-	**(0.034)**	(0.067)	(0.880)
GETS-SIS-DDD	**-2.544**	**-3.176**	**-4.366**	**-2.260**	2.774	2.720	1.853	1.303	1.884	-	-0.439	2.126
	(0.008)	**(0.002)**	**(0.000)**	**(0.016)**	(0.995)	(0.995)	(0.963)	(0.899)	(0.966)	-	(0.332)	(0.979)
Ridge, CV	**-2.401**	**-2.762**	**-4.081**	**-2.424**	2.149	2.217	0.644	0.476	1.542	0.439	-	2.239
	(0.011)	**(0.005)**	**(0.000)**	**(0.011)**	(0.980)	(0.983)	(0.738)	(0.681)	(0.933)	(0.668)	-	(0.984)
Lasso, CV	**-2.968**	**-3.359**	**-4.515**	**-2.691**	0.444	0.708	**-1.791**	**-2.130**	-1.196	**-2.126**	**-2.239**	-
	(0.003)	**(0.001)**	**(0.000)**	**(0.006)**	(0.670)	(0.758)	**(0.042)**	**(0.021)**	(0.120)	**(0.021)**	**(0.016)**	-
ELNET, CV	**-2.962**	**-3.355**	**-4.514**	**-2.688**	0.552	0.844	**-1.769**	**-2.109**	-1.141	**-2.106**	**-2.224**	2.056
	(0.003)	**(0.001)**	**(0.000)**	**(0.006)**	(0.708)	(0.797)	**(0.043)**	**(0.022)**	(0.131)	**(0.022)**	**(0.017)**	(0.976)
Ridge, AIC	**-2.491**	**-2.855**	**-4.163**	**-2.496**	1.926	1.991	0.427	0.250	1.305	0.215	-1.293	1.980
	(0.009)	**(0.004)**	**(0.000)**	**(0.009)**	(0.968)	(0.972)	(0.664)	(0.598)	(0.899)	(0.584)	(0.103)	(0.972)
Lasso, AIC	**-2.943**	**-3.365**	**-4.574**	**-2.678**	0.876	1.263	**-2.015**	**-2.384**	-1.277	**-2.368**	**-2.170**	0.071
	(0.003)	**(0.001)**	**(0.000)**	**(0.006)**	(0.806)	(0.892)	**(0.026)**	**(0.012)**	(0.106)	**(0.012)**	**(0.019)**	(0.528)
ELNET, AIC	**-2.932**	**-3.361**	**-4.562**	**-2.680**	0.668	1.137	**-2.067**	**-2.459**	-1.444	**-2.438**	**-2.205**	-0.136
	(0.003)	**(0.001)**	**(0.000)**	**(0.006)**	(0.746)	(0.868)	**(0.024)**	**(0.010)**	(0.079)	**(0.010)**	**(0.018)**	(0.446)
k-NN	-0.048	-1.101	**-2.063**	-0.317	3.033	3.036	2.844	2.743	2.813	2.739	2.353	3.015
	(0.481)	(0.140)	**(0.024)**	(0.377)	(0.998)	(0.998)	(0.996)	(0.995)	(0.996)	(0.995)	(0.987)	(0.997)
wk-NN	-0.016	-1.101	**-2.062**	-0.302	3.065	3.067	2.886	2.780	2.846	2.776	2.371	3.040
	(0.493)	(0.140)	**(0.024)**	(0.382)	(0.998)	(0.998)	(0.996)	(0.995)	(0.996)	(0.995)	(0.988)	(0.998)
RF	**-2.885**	**-3.125**	**-4.322**	**-2.449**	1.409	1.470	-0.236	-0.439	0.714	-0.473	-0.862	1.406
	(0.004)	**(0.002)**	**(0.000)**	**(0.010)**	(0.916)	(0.924)	(0.408)	(0.332)	(0.760)	(0.320)	(0.198)	(0.915)
FFNN	**-2.558**	**-2.988**	**-4.141**	**-2.315**	2.650	2.807	0.248	-0.055	1.858	-0.109	-0.619	2.654
	(0.008)	**(0.003)**	**(0.000)**	**(0.014)**	(0.994)	(0.996)	(0.597)	(0.478)	(0.964)	(0.457)	(0.270)	(0.994)
RNN	-0.559	-0.964	**-2.307**	-0.898	3.516	3.538	2.758	2.673	3.271	2.650	3.510	3.567
	(0.290)	(0.171)	**(0.014)**	(0.188)	(0.999)	(0.999)	(0.995)	(0.994)	(0.999)	(0.994)	(0.999)	(0.999)
SVR-LIN	**-2.284**	**-2.739**	**-3.961**	**-2.261**	2.091	2.135	0.775	0.584	1.514	0.545	0.095	2.055
	(0.015)	**(0.005)**	**(0.000)**	**(0.015)**	(0.978)	(0.980)	(0.778)	(0.718)	(0.930)	(0.705)	(0.538)	(0.976)
SVR-POLY	**-2.250**	**-2.659**	**-4.142**	**-2.281**	2.648	2.695	1.228	1.049	2.104	1.008	1.572	2.676
	(0.016)	**(0.006)**	**(0.000)**	**(0.015)**	(0.994)	(0.994)	(0.886)	(0.849)	(0.978)	(0.839)	(0.937)	(0.994)
SVR-RBF	**-2.222**	**-2.249**	**-3.710**	**-1.943**	2.279	2.303	1.556	1.438	1.944	1.417	1.592	2.358
	(0.017)	**(0.016)**	**(0.000)**	**(0.031)**	(0.985)	(0.986)	(0.935)	(0.920)	(0.969)	(0.917)	(0.939)	(0.988)
SVR-ANOVA	**-1.859**	**-2.327**	**-3.974**	**-1.896**	3.389	3.394	2.099	1.922	2.921	1.877	2.197	3.209
	(0.036)	**(0.013)**	**(0.000)**	**(0.034)**	(0.999)	(0.999)	(0.978)	(0.968)	(0.997)	(0.965)	(0.982)	(0.998)
AR+SVR-POLY	**-2.009**	**-2.351**	**-3.687**	**-1.975**	2.818	2.863	1.571	1.420	2.237	1.386	1.223	2.931
	(0.027)	**(0.013)**	**(0.000)**	**(0.029)**	(0.996)	(0.996)	(0.937)	(0.917)	(0.984)	(0.912)	(0.885)	(0.997)
AR+SVR-RBF	-1.181	-1.477	**-2.932**	-1.245	3.127	3.154	2.395	2.270	2.770	2.249	2.509	3.238
	(0.123)	(0.075)	**(0.003)**	(0.111)	(0.998)	(0.998)	(0.989)	(0.985)	(0.995)	(0.984)	(0.991)	(0.999)
AR+SVR-ANOVA	**-2.167**	**-2.542**	**-3.751**	**-2.056**	2.393	2.447	1.111	0.949	1.803	0.915	0.544	2.441
	(0.019)	**(0.008)**	**(0.000)**	**(0.024)**	(0.989)	(0.990)	(0.862)	(0.825)	(0.959)	(0.816)	(0.705)	(0.990)
AR+FFNN	**-2.037**	**-2.347**	**-3.659**	**-2.021**	2.745	2.787	1.660	1.511	2.236	1.481	1.338	2.891
	(0.025)	**(0.013)**	**(0.000)**	**(0.026)**	(0.995)	(0.995)	(0.946)	(0.930)	(0.984)	(0.926)	(0.905)	(0.997)
AR+RNN	1.018	0.501	-0.723	0.697	3.427	3.436	3.022	2.961	3.241	2.949	3.337	3.455
	(0.842)	(0.690)	(0.237)	(0.754)	(0.999)	(0.999)	(0.998)	(0.997)	(0.999)	(0.997)	(0.999)	(0.999)
Ave. BM	0.300	-0.870	**-2.492**	-0.320	3.523	3.534	3.209	3.105	3.278	3.093	3.034	3.574
	(0.617)	(0.195)	**(0.009)**	(0.375)	(0.999)	(0.999)	(0.998)	(0.998)	(0.999)	(0.998)	(0.998)	(0.999)
Ave. Linear	**-2.869**	**-3.313**	**-4.532**	**-2.613**	2.244	2.850	**-1.869**	**-2.322**	-0.917	**-2.303**	**-2.006**	1.053
	(0.004)	**(0.001)**	**(0.000)**	**(0.007)**	(0.984)	(0.996)	**(0.036)**	**(0.013)**	(0.183)	**(0.014)**	**(0.027)**	(0.850)
Ave. Local	**-2.517**	**-2.963**	**-3.744**	-1.653	3.024	3.028	2.432	2.219	2.539	2.201	1.601	3.014
	(0.009)	**(0.003)**	**(0.000)**	(0.054)	(0.998)	(0.998)	(0.989)	(0.983)	(0.992)	(0.982)	(0.940)	(0.997)
Ave. Non-linear	**-2.446**	**-2.777**	**-4.134**	**-2.379**	2.300	2.366	0.777	0.602	1.683	0.564	0.426	2.411
	(0.010)	**(0.005)**	**(0.000)**	**(0.012)**	(0.986)	(0.988)	(0.779)	(0.724)	(0.949)	(0.712)	(0.663)	(0.989)
Ave. AR+	-1.666	**-1.945**	**-3.319**	-1.695	2.711	2.742	1.821	1.698	2.299	1.673	1.791	2.802
	(0.053)	**(0.030)**	**(0.001)**	(0.050)	(0.995)	(0.995)	(0.961)	(0.950)	(0.986)	(0.948)	(0.958)	(0.996)
Tot. Ave.	**-2.812**	**-3.146**	**-4.427**	**-2.554**	2.406	2.493	0.293	0.066	1.353	0.025	-0.717	2.708
	(0.004)	**(0.002)**	**(0.000)**	**(0.008)**	(0.989)	(0.991)	(0.614)	(0.526)	(0.907)	(0.510)	(0.239)	(0.995)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.44: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 0$. $N = 32$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	2.962	2.491	2.943	2.932	0.048	0.016	2.885	2.558	0.559	2.284	2.250	2.222
	(0.997)	(0.991)	(0.997)	(0.997)	(0.519)	(0.507)	(0.996)	(0.992)	(0.710)	(0.985)	(0.984)	(0.983)
RW	3.355	2.855	3.365	3.361	1.101	1.101	3.125	2.988	0.964	2.739	2.659	2.249
	(0.999)	(0.996)	(0.999)	(0.999)	(0.860)	(0.860)	(0.998)	(0.997)	(0.829)	(0.995)	(0.994)	(0.984)
DDD	4.514	4.163	4.574	4.562	2.063	2.062	4.322	4.141	2.307	3.961	4.142	3.710
	(1.000)	(1.000)	(1.000)	(1.000)	(0.976)	(0.976)	(1.000)	(1.000)	(0.986)	(1.000)	(1.000)	(1.000)
VAR(4)	2.688	2.496	2.678	2.680	0.317	0.302	2.449	2.315	0.898	2.261	2.281	1.943
	(0.994)	(0.991)	(0.994)	(0.994)	(0.623)	(0.618)	(0.990)	(0.986)	(0.812)	(0.985)	(0.985)	(0.969)
GETS	-0.552	**-1.926**	-0.876	-0.668	**-3.033**	**-3.065**	-1.409	**-2.650**	**-3.516**	**-2.091**	**-2.648**	**-2.279**
	(0.292)	**(0.032)**	(0.194)	(0.254)	**(0.002)**	**(0.002)**	(0.084)	**(0.006)**	**(0.001)**	**(0.022)**	**(0.006)**	**(0.015)**
GETS-IIS	-0.844	**-1.991**	-1.263	-1.137	**-3.036**	**-3.067**	-1.470	**-2.807**	**-3.538**	**-2.135**	**-2.695**	**-2.303**
	(0.203)	**(0.028)**	(0.108)	(0.132)	**(0.002)**	**(0.002)**	(0.076)	**(0.004)**	**(0.001)**	**(0.020)**	**(0.006)**	**(0.014)**
GETS-SIS	1.769	-0.427	2.015	2.067	**-2.844**	**-2.886**	0.236	-0.248	**-2.758**	-0.775	-1.228	-1.556
	(0.957)	(0.336)	(0.974)	(0.976)	**(0.004)**	**(0.004)**	(0.592)	(0.403)	**(0.005)**	(0.222)	(0.114)	(0.065)
GETS-DDD	2.109	-0.250	2.384	2.459	**-2.743**	**-2.780**	0.439	0.055	**-2.673**	-0.584	-1.049	-1.438
	(0.978)	(0.402)	(0.988)	(0.990)	**(0.005)**	**(0.005)**	(0.668)	(0.522)	**(0.006)**	(0.282)	(0.151)	(0.080)
GETS-IIS-DDD	1.141	-1.305	1.277	1.444	**-2.813**	**-2.846**	-0.714	**-1.858**	**-3.271**	-1.514	**-2.104**	**-1.944**
	(0.869)	(0.101)	(0.894)	(0.921)	**(0.004)**	**(0.004)**	(0.240)	**(0.036)**	**(0.001)**	(0.070)	**(0.022)**	**(0.031)**
GETS-SIS-DDD	2.106	-0.215	2.368	2.438	**-2.739**	**-2.776**	0.473	0.109	**-2.650**	-0.545	-1.008	-1.417
	(0.978)	(0.416)	(0.988)	(0.990)	**(0.005)**	**(0.005)**	(0.680)	(0.543)	**(0.006)**	(0.295)	(0.161)	(0.083)
Ridge, CV	2.224	1.293	2.170	2.205	**-2.353**	**-2.371**	0.862	0.619	**-3.510**	-0.095	-1.572	-1.592
	(0.983)	(0.897)	(0.981)	(0.982)	**(0.013)**	**(0.012)**	(0.802)	(0.730)	**(0.001)**	(0.462)	(0.063)	(0.061)
Lasso, CV	**-2.056**	**-1.980**	-0.071	0.136	**-3.015**	**-3.040**	-1.406	**-2.654**	**-3.567**	**-2.055**	**-2.676**	**-2.358**
	(0.024)	**(0.028)**	(0.472)	(0.554)	**(0.003)**	**(0.002)**	(0.085)	**(0.006)**	**(0.001)**	**(0.024)**	**(0.006)**	**(0.012)**
ELNET, CV	-	**-1.964**	0.101	0.314	**-3.010**	**-3.035**	-1.376	**-2.617**	**-3.562**	**-2.039**	**-2.667**	**-2.350**
	-	**(0.029)**	(0.540)	(0.622)	**(0.003)**	**(0.002)**	(0.089)	**(0.007)**	**(0.001)**	**(0.025)**	**(0.006)**	**(0.013)**
Ridge, AIC	1.964	-	1.932	1.967	**-2.444**	**-2.464**	0.640	0.350	**-3.736**	-0.519	**-2.485**	**-1.767**
	(0.971)	-	(0.969)	(0.971)	**(0.010)**	**(0.010)**	(0.737)	(0.636)	**(0.000)**	(0.304)	**(0.009)**	**(0.044)**
Lasso, AIC	-0.101	**-1.932**	-	0.602	**-3.018**	**-3.046**	-1.360	**-2.569**	**-3.524**	**-2.037**	**-2.678**	**-2.324**
	(0.460)	**(0.031)**	-	(0.724)	**(0.003)**	**(0.002)**	(0.092)	**(0.008)**	**(0.001)**	**(0.025)**	**(0.006)**	**(0.013)**
ELNET, AIC	-0.314	**-1.967**	-0.602	-	**-3.012**	**-3.040**	-1.347	**-2.617**	**-3.542**	**-2.078**	**-2.690**	**-2.303**
	(0.378)	**(0.029)**	(0.276)	-	**(0.003)**	**(0.002)**	(0.094)	**(0.007)**	**(0.001)**	**(0.023)**	**(0.006)**	**(0.014)**
k-NN	3.010	2.444	3.018	3.012	-	-0.120	2.775	2.542	0.535	2.275	2.158	1.698
	(0.997)	(0.990)	(0.997)	(0.997)	-	(0.453)	(0.995)	(0.992)	(0.702)	(0.985)	(0.981)	(0.950)
wk-NN	3.035	2.464	3.046	3.040	0.120	-	2.810	2.573	0.551	2.295	2.185	1.707
	(0.998)	(0.990)	(0.998)	(0.998)	(0.547)	-	(0.996)	(0.992)	(0.707)	(0.986)	(0.982)	(0.951)
RF	1.376	-0.640	1.360	1.347	**-2.775**	**-2.810**	-	-0.609	**-2.988**	-0.837	-1.478	**-2.169**
	(0.911)	(0.263)	(0.908)	(0.906)	**(0.005)**	**(0.004)**	-	(0.274)	**(0.003)**	(0.205)	(0.075)	**(0.019)**
FFNN	2.617	-0.350	2.569	2.617	**-2.542**	**-2.573**	0.609	-	**-2.979**	-0.770	-1.316	-1.657
	(0.993)	(0.364)	(0.992)	(0.993)	**(0.008)**	**(0.008)**	(0.726)	-	**(0.003)**	(0.223)	(0.099)	(0.054)
RNN	3.562	3.736	3.524	3.542	-0.535	-0.551	2.988	2.979	-	3.238	2.986	1.315
	(0.999)	(1.000)	(0.999)	(0.999)	(0.298)	(0.293)	(0.997)	(0.997)	-	(0.999)	(0.997)	(0.901)
SVR-LIN	2.039	0.519	2.037	2.078	**-2.275**	**-2.295**	0.837	0.770	**-3.238**	-	-0.873	-1.338
	(0.975)	(0.696)	(0.975)	(0.977)	**(0.015)**	**(0.014)**	(0.795)	(0.777)	**(0.001)**	-	(0.195)	(0.095)
SVR-POLY	2.667	2.485	2.678	2.690	**-2.158**	**-2.185**	1.478	1.316	**-2.986**	0.873	-	-1.297
	(0.994)	(0.991)	(0.994)	(0.994)	**(0.019)**	**(0.018)**	(0.925)	(0.901)	**(0.003)**	(0.805)	-	(0.102)
SVR-RBF	2.350	1.767	2.324	2.303	**-1.698**	**-1.707**	2.169	1.657	-1.315	1.338	1.297	-
	(0.987)	(0.956)	(0.987)	(0.986)	**(0.050)**	**(0.049)**	(0.981)	(0.946)	(0.099)	(0.905)	(0.898)	-
SVR-ANOVA	3.208	2.666	3.327	3.339	**-1.841**	**-1.868**	2.063	2.060	**-2.262**	1.907	1.887	-0.614
	(0.998)	(0.994)	(0.999)	(0.999)	**(0.038)**	**(0.036)**	(0.976)	(0.976)	**(0.015)**	(0.967)	(0.966)	(0.272)
AR+SVR-POLY	2.912	1.467	2.854	2.839	**-1.878**	**-1.906**	2.098	1.694	**-1.928**	1.064	0.697	-0.620
	(0.997)	(0.924)	(0.996)	(0.996)	**(0.035)**	**(0.033)**	(0.978)	(0.950)	**(0.032)**	(0.852)	(0.755)	(0.270)
AR+SVR-RBF	3.228	2.672	3.181	3.155	-0.946	-0.967	3.136	2.557	-0.422	2.225	2.226	1.631
	(0.999)	(0.994)	(0.998)	(0.998)	(0.176)	(0.170)	(0.998)	(0.992)	(0.338)	(0.983)	(0.983)	(0.944)
AR+SVR-ANOVA	2.417	0.769	2.367	2.377	**-2.089**	**-2.121**	1.383	1.154	**-2.255**	0.488	0.036	-0.961
	(0.989)	(0.776)	(0.988)	(0.988)	**(0.022)**	**(0.021)**	(0.912)	(0.871)	**(0.016)**	(0.686)	(0.514)	(0.172)
AR+FFNN	2.873	1.549	2.808	2.790	**-1.828**	**-1.856**	2.284	1.764	-1.621	1.160	0.891	-0.420
	(0.996)	(0.934)	(0.996)	(0.996)	**(0.039)**	**(0.037)**	(0.985)	(0.956)	(0.058)	(0.873)	(0.810)	(0.339)
AR+RNN	3.451	3.406	3.441	3.431	0.913	0.922	3.352	3.144	1.802	3.157	3.204	3.072
	(0.999)	(0.999)	(0.999)	(0.999)	(0.816)	(0.818)	(0.999)	(0.998)	(0.959)	(0.998)	(0.998)	(0.998)
Ave. BM	3.570	3.150	3.566	3.554	0.247	0.224	3.341	3.046	0.781	2.830	2.919	2.753
	(0.999)	(0.998)	(0.999)	(0.999)	(0.597)	(0.588)	(0.999)	(0.998)	(0.780)	(0.996)	(0.997)	(0.995)
Ave. Linear	0.970	**-1.764**	1.575	1.994	**-2.946**	**-2.977**	-1.066	**-2.449**	**-3.458**	**-1.944**	**-2.591**	**-2.194**
	(0.830)	**(0.044)**	(0.937)	(0.972)	**(0.003)**	**(0.003)**	(0.147)	**(0.010)**	**(0.001)**	**(0.031)**	**(0.007)**	**(0.018)**
Ave. Local	3.003	1.770	3.020	2.991	**-2.803**	**-2.830**	2.582	2.039	-1.052	1.469	1.258	0.171
	(0.997)	(0.957)	(0.997)	(0.997)	**(0.004)**	**(0.004)**	(0.993)	(0.975)	(0.150)	(0.924)	(0.891)	(0.567)
Ave. Non-linear	2.397	1.476	2.340	2.349	**-2.344**	**-2.366**	1.128	0.845	**-3.500**	0.127	-1.455	-1.692
	(0.989)	(0.925)	(0.987)	(0.987)	**(0.013)**	**(0.012)**	(0.866)	(0.798)	**(0.001)**	(0.550)	(0.078)	(0.050)
Ave. AR+	2.789	1.985	2.746	2.730	-1.460	-1.486	2.391	1.976	-1.279	1.579	1.392	0.139
	(0.996)	(0.972)	(0.995)	(0.995)	(0.077)	(0.074)	(0.988)	(0.971)	(0.105)	(0.938)	(0.913)	(0.555)
Tot. Ave.	2.682	-0.344	2.592	2.522	**-2.714**	**-2.741**	0.725	0.139	**-3.132**	-0.596	-1.666	**-2.153**
	(0.994)	(0.367)	(0.993)	(0.991)	**(0.005)**	**(0.005)**	(0.763)	(0.555)	**(0.002)**	(0.278)	(0.053)	**(0.020)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.45: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 0$. $N = 32$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	1.859	2.009	1.181	2.167	2.037	-1.018	-0.300	2.869	2.517	2.446	1.666	2.812
	(0.964)	(0.973)	(0.877)	(0.981)	(0.975)	(0.158)	(0.383)	(0.996)	(0.991)	(0.990)	(0.947)	(0.996)
RW	2.327	2.351	1.477	2.542	2.347	-0.501	0.870	3.313	2.963	2.777	1.945	3.146
	(0.987)	(0.987)	(0.925)	(0.992)	(0.987)	(0.310)	(0.805)	(0.999)	(0.997)	(0.995)	(0.970)	(0.998)
DDD	3.974	3.687	2.932	3.751	3.659	0.723	2.492	4.532	3.744	4.134	3.319	4.427
	(1.000)	(1.000)	(0.997)	(1.000)	(1.000)	(0.763)	(0.991)	(1.000)	(1.000)	(1.000)	(0.999)	(1.000)
VAR(4)	1.896	1.975	1.245	2.056	2.021	-0.697	0.320	2.613	1.653	2.379	1.695	2.554
	(0.966)	(0.971)	(0.889)	(0.976)	(0.974)	(0.246)	(0.625)	(0.993)	(0.946)	(0.988)	(0.950)	(0.992)
GETS	**-3.389**	**-2.818**	**-3.127**	**-2.393**	**-2.745**	**-3.427**	**-3.523**	**-2.244**	**-3.024**	**-2.300**	**-2.711**	**-2.406**
	(0.001)	**(0.004)**	**(0.002)**	**(0.011)**	**(0.005)**	**(0.001)**	**(0.001)**	**(0.016)**	**(0.002)**	**(0.014)**	**(0.005)**	**(0.011)**
GETS-IIS	**-3.394**	**-2.863**	**-3.154**	**-2.447**	**-2.787**	**-3.436**	**-3.534**	**-2.850**	**-3.028**	**-2.366**	**-2.742**	**-2.493**
	(0.001)	**(0.004)**	**(0.002)**	**(0.010)**	**(0.005)**	**(0.001)**	**(0.001)**	**(0.004)**	**(0.002)**	**(0.012)**	**(0.005)**	**(0.009)**
GETS-SIS	**-2.099**	-1.571	**-2.395**	-1.111	-1.660	**-3.022**	**-3.209**	1.869	**-2.432**	-0.777	**-1.821**	-0.293
	(0.022)	(0.063)	**(0.011)**	(0.138)	(0.054)	**(0.002)**	**(0.002)**	(0.964)	**(0.011)**	(0.221)	**(0.039)**	(0.386)
GETS-DDD	**-1.922**	-1.420	**-2.270**	-0.949	-1.511	**-2.961**	**-3.105**	2.322	**-2.219**	-0.602	**-1.698**	-0.066
	(0.032)	(0.083)	**(0.015)**	(0.175)	(0.070)	**(0.003)**	**(0.002)**	(0.987)	**(0.017)**	(0.276)	**(0.050)**	(0.474)
GETS-IIS-DDD	**-2.921**	**-2.237**	**-2.770**	**-1.803**	**-2.236**	**-3.241**	**-3.278**	0.917	**-2.539**	-1.683	**-2.299**	-1.353
	(0.003)	**(0.016)**	**(0.005)**	**(0.041)**	**(0.016)**	**(0.001)**	**(0.001)**	(0.817)	**(0.008)**	(0.051)	**(0.014)**	(0.093)
GETS-SIS-DDD	**-1.877**	-1.386	**-2.249**	-0.915	-1.481	**-2.949**	**-3.093**	2.303	**-2.201**	-0.564	-1.673	-0.025
	(0.035)	(0.088)	**(0.016)**	(0.184)	(0.074)	**(0.003)**	**(0.002)**	(0.986)	**(0.018)**	(0.288)	(0.052)	(0.490)
Ridge, CV	**-2.197**	-1.223	**-2.509**	-0.544	-1.338	**-3.337**	**-3.034**	2.006	-1.601	-0.426	**-1.791**	0.717
	(0.018)	(0.115)	**(0.009)**	(0.295)	(0.095)	**(0.001)**	**(0.002)**	(0.973)	(0.060)	(0.337)	**(0.042)**	(0.761)
Lasso, CV	**-3.209**	**-2.931**	**-3.238**	**-2.441**	**-2.891**	**-3.455**	**-3.574**	-1.053	**-3.014**	**-2.411**	**-2.802**	**-2.708**
	(0.002)	**(0.003)**	**(0.001)**	**(0.010)**	**(0.003)**	**(0.001)**	**(0.001)**	(0.150)	**(0.003)**	**(0.011)**	**(0.004)**	**(0.005)**
ELNET, CV	**-3.208**	**-2.912**	**-3.228**	**-2.417**	**-2.873**	**-3.451**	**-3.570**	-0.970	**-3.003**	**-2.397**	**-2.789**	**-2.682**
	(0.002)	**(0.003)**	**(0.001)**	**(0.011)**	**(0.004)**	**(0.001)**	**(0.001)**	(0.170)	**(0.003)**	**(0.011)**	**(0.004)**	**(0.006)**
Ridge, AIC	**-2.666**	-1.467	**-2.672**	-0.769	-1.549	**-3.406**	**-3.150**	1.764	**-1.770**	-1.476	**-1.985**	0.344
	(0.006)	(0.076)	**(0.006)**	(0.224)	(0.066)	**(0.001)**	**(0.002)**	(0.956)	**(0.043)**	(0.075)	**(0.028)**	(0.633)
Lasso, AIC	**-3.327**	**-2.854**	**-3.181**	**-2.367**	**-2.808**	**-3.441**	**-3.566**	-1.575	**-3.020**	**-2.340**	**-2.746**	**-2.592**
	(0.001)	**(0.004)**	**(0.002)**	**(0.012)**	**(0.004)**	**(0.001)**	**(0.001)**	(0.063)	**(0.003)**	**(0.013)**	**(0.005)**	**(0.007)**
ELNET, AIC	**-3.339**	**-2.839**	**-3.155**	**-2.377**	**-2.790**	**-3.431**	**-3.554**	**-1.994**	**-2.991**	**-2.349**	**-2.730**	**-2.522**
	(0.001)	**(0.004)**	**(0.002)**	**(0.012)**	**(0.004)**	**(0.001)**	**(0.001)**	**(0.028)**	**(0.003)**	**(0.013)**	**(0.005)**	**(0.009)**
k-NN	1.841	1.878	0.946	2.089	1.828	-0.913	-0.247	2.946	2.803	2.344	1.460	2.714
	(0.962)	(0.965)	(0.824)	(0.978)	(0.961)	(0.184)	(0.403)	(0.997)	(0.996)	(0.987)	(0.923)	(0.995)
wk-NN	1.868	1.906	0.967	2.121	1.856	-0.922	-0.224	2.977	2.830	2.366	1.486	2.741
	(0.964)	(0.967)	(0.830)	(0.979)	(0.963)	(0.182)	(0.412)	(0.997)	(0.996)	(0.988)	(0.926)	(0.995)
RF	**-2.063**	**-2.098**	**-3.136**	-1.383	**-2.284**	**-3.352**	**-3.341**	1.066	**-2.582**	-1.128	**-2.391**	-0.725
	(0.024)	**(0.022)**	**(0.002)**	(0.088)	**(0.015)**	**(0.001)**	**(0.001)**	(0.853)	**(0.007)**	(0.134)	**(0.012)**	(0.237)
FFNN	**-2.060**	-1.694	**-2.557**	-1.154	**-1.764**	**-3.144**	**-3.046**	2.449	**-2.039**	-0.845	**-1.976**	-0.139
	(0.024)	(0.050)	**(0.008)**	(0.129)	**(0.044)**	**(0.002)**	**(0.002)**	(0.990)	**(0.025)**	(0.202)	**(0.029)**	(0.445)
RNN	2.262	1.928	0.422	2.255	1.621	**-1.802**	-0.781	3.458	1.052	3.500	1.279	3.132
	(0.985)	(0.968)	(0.662)	(0.984)	(0.942)	**(0.041)**	(0.220)	(0.999)	(0.850)	(0.999)	(0.895)	(0.998)
SVR-LIN	**-1.907**	-1.064	**-2.225**	-0.488	-1.160	**-3.157**	**-2.830**	1.944	-1.469	-0.127	-1.579	0.596
	(0.033)	(0.148)	**(0.017)**	(0.314)	(0.127)	**(0.002)**	**(0.004)**	(0.969)	(0.076)	(0.450)	(0.062)	(0.722)
SVR-POLY	**-1.887**	-0.697	**-2.226**	-0.036	-0.891	**-3.204**	**-2.919**	2.591	-1.258	1.455	-1.392	1.666
	(0.034)	(0.245)	**(0.017)**	(0.486)	(0.190)	**(0.002)**	**(0.003)**	(0.993)	(0.109)	(0.922)	(0.087)	(0.947)
SVR-RBF	0.614	0.620	-1.631	0.961	0.420	**-3.072**	**-2.753**	2.194	-0.171	1.692	-0.139	2.153
	(0.728)	(0.730)	(0.056)	(0.828)	(0.661)	**(0.002)**	**(0.005)**	(0.982)	(0.433)	(0.950)	(0.445)	(0.980)
SVR-ANOVA	-	-0.009	-1.498	0.542	-0.230	**-2.816**	**-2.388**	3.354	-0.714	2.061	-0.694	2.163
	-	(0.496)	(0.072)	(0.704)	(0.410)	**(0.004)**	**(0.012)**	(0.999)	(0.240)	(0.976)	(0.246)	(0.981)
AR+SVR-POLY	0.009	-	**-2.767**	1.743	-0.808	**-3.264**	**-2.487**	2.620	-0.753	1.135	**-2.052**	2.049
	(0.504)	-	**(0.005)**	(0.954)	(0.213)	**(0.001)**	**(0.009)**	(0.993)	(0.229)	(0.867)	**(0.024)**	(0.976)
AR+SVR-RBF	1.498	2.767	-	2.692	2.733	**-2.783**	-1.488	3.037	0.937	2.587	2.703	3.151
	(0.928)	(0.995)	-	(0.994)	(0.995)	**(0.005)**	(0.073)	(0.998)	(0.822)	(0.993)	(0.994)	(0.998)
AR+SVR-ANOVA	-0.542	**-1.743**	**-2.692**	-	-1.525	**-3.249**	**-2.597**	2.156	-1.166	0.424	**-2.185**	1.119
	(0.296)	**(0.046)**	**(0.006)**	-	(0.069)	**(0.001)**	**(0.007)**	(0.981)	(0.126)	(0.663)	**(0.018)**	(0.864)
AR+FFNN	0.230	0.808	**-2.733**	1.525	-	**-3.125**	**-2.592**	2.579	-0.567	1.274	-1.357	2.246
	(0.590)	(0.787)	**(0.005)**	(0.931)	-	**(0.002)**	**(0.007)**	(0.993)	(0.287)	(0.894)	(0.092)	(0.984)
AR+RNN	2.816	3.264	2.783	3.249	3.125	-	0.961	3.382	2.334	3.349	3.407	3.417
	(0.996)	(0.999)	(0.995)	(0.999)	(0.998)	-	(0.828)	(0.999)	(0.987)	(0.999)	(0.999)	(0.999)
Ave. BM	2.388	2.487	1.488	2.597	2.592	-0.961	-	3.476	2.861	3.067	2.057	3.526
	(0.988)	(0.991)	(0.927)	(0.993)	(0.993)	(0.172)	-	(0.999)	(0.996)	(0.998)	(0.976)	(0.999)
Ave. Linear	**-3.354**	**-2.620**	**-3.037**	**-2.156**	**-2.579**	**-3.382**	**-3.476**	-	**-2.845**	**-2.173**	**-2.586**	**-2.121**
	(0.001)	**(0.007)**	**(0.002)**	**(0.019)**	**(0.007)**	**(0.001)**	**(0.001)**	-	**(0.004)**	**(0.019)**	**(0.007)**	**(0.021)**
Ave. Local	0.714	0.753	-0.937	1.166	0.567	**-2.334**	**-2.861**	2.845	-	1.598	0.038	2.440
	(0.760)	(0.771)	(0.178)	(0.874)	(0.713)	**(0.013)**	**(0.004)**	(0.996)	-	(0.940)	(0.515)	(0.990)
Ave. Non-linear	**-2.061**	-1.135	**-2.587**	-0.424	-1.274	**-3.349**	**-3.067**	2.173	-1.598	-	**-1.769**	1.115
	(0.024)	(0.133)	**(0.007)**	(0.337)	(0.106)	**(0.001)**	**(0.002)**	(0.981)	(0.060)	-	**(0.043)**	(0.863)
Ave. AR+	0.694	2.052	**-2.703**	2.185	1.357	**-3.407**	**-2.057**	2.586	-0.038	1.769	-	2.406
	(0.754)	(0.976)	**(0.006)**	(0.982)	(0.908)	**(0.001)**	**(0.024)**	(0.993)	(0.485)	(0.957)	-	(0.989)
Tot. Ave.	**-2.163**	**-2.049**	**-3.151**	-1.119	**-2.246**	**-3.417**	**-3.526**	2.121	**-2.440**	-1.115	**-2.406**	-
	(0.019)	**(0.024)**	**(0.002)**	(0.136)	**(0.016)**	**(0.001)**	**(0.001)**	(0.979)	**(0.010)**	(0.137)	**(0.011)**	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.46: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 1$. $N = 31$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.781	**-2.501**	-0.811	-1.603	-1.408	**-2.125**	**-3.570**	**-3.338**	**-3.423**	-0.443	-1.560
	-	(0.221)	**(0.009)**	(0.212)	(0.060)	(0.085)	**(0.021)**	**(0.001)**	**(0.001)**	**(0.001)**	(0.330)	(0.065)
RW	0.781	-	**-2.729**	-0.360	-1.230	-0.979	-1.672	**-2.893**	**-2.707**	**-2.795**	0.200	-0.764
	(0.779)	-	**(0.005)**	(0.361)	(0.114)	(0.168)	(0.052)	**(0.004)**	**(0.006)**	**(0.004)**	(0.579)	(0.225)
DDD	2.501	2.729	-	1.662	-0.081	0.295	-0.106	-1.201	-0.776	-0.759	2.129	1.483
	(0.991)	(0.995)	-	(0.947)	(0.468)	(0.615)	(0.458)	(0.120)	(0.222)	(0.227)	(0.979)	(0.926)
VAR(4)	0.811	0.360	-1.662	-	-1.230	-0.874	-1.601	**-2.609**	**-2.166**	**-2.176**	0.669	-0.572
	(0.788)	(0.639)	(0.053)	-	(0.114)	(0.194)	(0.060)	**(0.007)**	**(0.019)**	**(0.019)**	(0.746)	(0.286)
GETS	1.603	1.230	0.081	1.230	-	1.918	0.001	-1.167	-0.585	-0.539	1.802	1.245
	(0.940)	(0.886)	(0.532)	(0.886)	-	(0.968)	(0.501)	(0.126)	(0.281)	(0.297)	(0.959)	(0.889)
GETS-IIS	1.408	0.979	-0.295	0.874	**-1.918**	-	-0.732	**-1.894**	-1.192	-1.089	1.537	0.863
	(0.915)	(0.832)	(0.385)	(0.806)	**(0.032)**	-	(0.235)	**(0.034)**	(0.121)	(0.142)	(0.933)	(0.802)
GETS-SIS	2.125	1.672	0.106	1.601	-0.001	0.732	-	-1.660	-0.846	-0.754	2.578	1.703
	(0.979)	(0.948)	(0.542)	(0.940)	(0.499)	(0.765)	-	(0.054)	(0.202)	(0.228)	(0.992)	(0.951)
GETS-DDD	3.570	2.893	1.201	2.609	1.167	1.894	1.660	-	1.870	1.224	3.957	3.070
	(0.999)	(0.996)	(0.880)	(0.993)	(0.874)	(0.966)	(0.946)	-	(0.964)	(0.885)	(1.000)	(0.998)
GETS-IIS-DDD	3.338	2.707	0.776	2.166	0.585	1.192	0.846	**-1.870**	-	-0.007	3.452	2.526
	(0.999)	(0.994)	(0.778)	(0.981)	(0.719)	(0.879)	(0.798)	**(0.036)**	-	(0.497)	(0.999)	(0.991)
GETS-SIS-DDD	3.423	2.795	0.759	2.176	0.539	1.089	0.754	-1.224	0.007	-	3.417	2.489
	(0.999)	(0.996)	(0.773)	(0.981)	(0.703)	(0.858)	(0.772)	(0.115)	(0.503)	-	(0.999)	(0.991)
Ridge, CV	0.443	-0.200	**-2.129**	-0.669	**-1.802**	-1.537	**-2.578**	**-3.957**	**-3.452**	**-3.417**	-	**-2.416**
	(0.670)	(0.421)	**(0.021)**	(0.254)	**(0.041)**	(0.067)	**(0.008)**	**(0.000)**	**(0.001)**	**(0.001)**	-	**(0.011)**
Lasso, CV	1.560	0.764	-1.483	0.572	-1.245	-0.863	**-1.703**	**-3.070**	**-2.526**	**-2.489**	2.416	-
	(0.935)	(0.775)	(0.074)	(0.714)	(0.111)	(0.198)	**(0.049)**	**(0.002)**	**(0.009)**	**(0.009)**	(0.989)	-
ELNET, CV	0.834	0.138	**-1.947**	-0.380	-1.606	-1.278	**-2.257**	**-3.617**	**-3.073**	**-3.042**	1.223	**-2.646**
	(0.795)	(0.555)	**(0.030)**	(0.353)	(0.059)	(0.106)	**(0.016)**	**(0.001)**	**(0.002)**	**(0.002)**	(0.884)	**(0.006)**
Ridge, AIC	1.012	0.517	-1.096	0.290	**-2.127**	**-1.806**	**-2.136**	**-3.022**	**-2.308**	**-2.153**	1.132	0.079
	(0.840)	(0.695)	(0.141)	(0.613)	**(0.021)**	**(0.040)**	**(0.020)**	**(0.003)**	**(0.014)**	**(0.020)**	(0.867)	(0.531)
Lasso, AIC	1.277	1.036	0.083	1.033	0.046	0.758	0.026	-0.867	-0.445	-0.415	1.406	0.992
	(0.894)	(0.846)	(0.533)	(0.845)	(0.518)	(0.773)	(0.510)	(0.197)	(0.330)	(0.340)	(0.915)	(0.835)
ELNET, AIC	1.279	1.106	0.360	1.119	0.650	0.964	0.462	-0.302	-0.007	-0.007	1.370	1.074
	(0.895)	(0.861)	(0.639)	(0.864)	(0.740)	(0.829)	(0.676)	(0.382)	(0.497)	(0.497)	(0.910)	(0.854)
k-NN	0.580	-0.187	**-2.392**	-0.359	-1.280	-1.056	**-1.749**	**-2.953**	**-2.860**	**-2.975**	0.089	-0.780
	(0.717)	(0.426)	**(0.012)**	(0.361)	(0.105)	(0.150)	**(0.045)**	**(0.003)**	**(0.004)**	**(0.003)**	(0.535)	(0.221)
wk-NN	0.393	-0.354	**-2.483**	-0.416	-1.321	-1.105	**-1.844**	**-3.065**	**-2.981**	**-3.089**	-0.019	-0.840
	(0.651)	(0.363)	**(0.009)**	(0.340)	(0.098)	(0.139)	**(0.038)**	**(0.002)**	**(0.003)**	**(0.002)**	(0.492)	(0.204)
RF	2.107	0.565	-1.680	0.092	-1.244	-0.961	-1.605	**-3.205**	**-2.755**	**-2.767**	1.029	-0.344
	(0.978)	(0.712)	(0.052)	(0.536)	(0.112)	(0.172)	(0.059)	**(0.002)**	**(0.005)**	**(0.005)**	(0.844)	(0.367)
FFNN	0.591	-0.008	**-1.956**	-0.422	**-1.902**	-1.602	**-2.768**	**-4.076**	**-3.423**	**-3.322**	0.499	-1.441
	(0.721)	(0.497)	**(0.030)**	(0.338)	**(0.033)**	(0.060)	**(0.005)**	**(0.000)**	**(0.001)**	**(0.001)**	(0.689)	(0.080)
RNN	2.089	1.759	-0.069	1.352	-0.141	0.254	-0.188	-1.106	-0.745	-0.759	2.043	1.305
	(0.977)	(0.956)	(0.473)	(0.907)	(0.444)	(0.600)	(0.426)	(0.139)	(0.231)	(0.227)	(0.975)	(0.899)
SVR-LIN	1.291	0.447	-1.664	0.097	-1.554	-1.225	**-1.999**	**-3.441**	**-2.787**	**-2.722**	1.585	-0.455
	(0.897)	(0.671)	(0.053)	(0.539)	(0.065)	(0.115)	**(0.027)**	**(0.001)**	**(0.005)**	**(0.005)**	(0.938)	(0.326)
SVR-POLY	0.911	0.762	-0.055	0.753	-0.202	0.220	-0.178	-0.838	-0.505	-0.479	0.964	0.657
	(0.815)	(0.774)	(0.478)	(0.771)	(0.421)	(0.587)	(0.430)	(0.204)	(0.309)	(0.318)	(0.829)	(0.742)
SVR-RBF	-1.023	-1.279	**-2.873**	-1.337	**-2.027**	**-1.871**	**-2.890**	**-4.202**	**-3.924**	**-4.025**	**-1.919**	**-2.555**
	(0.157)	(0.105)	**(0.004)**	(0.096)	**(0.026)**	**(0.036)**	**(0.004)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.032)**	**(0.008)**
SVR-ANOVA	1.211	1.039	0.235	1.078	0.349	0.724	0.274	-0.522	-0.188	-0.177	1.301	0.995
	(0.882)	(0.847)	(0.592)	(0.855)	(0.635)	(0.763)	(0.607)	(0.303)	(0.426)	(0.430)	(0.898)	(0.836)
AR+SVR-POLY	0.980	0.540	-1.308	0.299	-1.550	-1.079	**-2.228**	**-3.099**	**-2.561**	**-2.466**	1.175	-0.001
	(0.833)	(0.703)	(0.100)	(0.617)	(0.066)	(0.145)	**(0.017)**	**(0.002)**	**(0.008)**	**(0.010)**	(0.875)	(0.500)
AR+SVR-RBF	0.553	-0.112	**-1.954**	-0.404	-1.548	-1.324	**-2.069**	**-3.552**	**-3.266**	**-3.476**	0.127	-0.986
	(0.708)	(0.456)	**(0.030)**	(0.344)	(0.066)	(0.098)	**(0.024)**	**(0.001)**	**(0.001)**	**(0.001)**	(0.550)	(0.166)
AR+SVR-ANOVA	-0.073	-0.645	**-2.365**	-0.911	-1.535	-1.311	**-2.177**	**-3.534**	**-3.357**	**-3.583**	-0.516	-1.605
	(0.471)	(0.262)	**(0.012)**	(0.185)	(0.068)	(0.100)	**(0.019)**	**(0.001)**	**(0.001)**	**(0.001)**	(0.305)	(0.059)
AR+FFNN	1.222	0.434	-1.444	0.099	-1.317	-1.035	-1.540	**-3.206**	**-2.616**	**-2.711**	0.908	-0.221
	(0.884)	(0.666)	(0.080)	(0.539)	(0.099)	(0.154)	(0.067)	**(0.002)**	**(0.007)**	**(0.005)**	(0.814)	(0.413)
AR+RNN	2.714	1.907	-0.521	1.192	-0.488	-0.043	-0.649	**-2.062**	-1.538	-1.453	2.459	1.290
	(0.995)	(0.967)	(0.303)	(0.879)	(0.314)	(0.483)	(0.261)	**(0.024)**	(0.067)	(0.078)	(0.990)	(0.897)
Ave. BM	0.751	-0.262	**-2.804**	-0.671	-1.407	-1.142	**-1.930**	**-3.184**	**-2.888**	**-2.929**	0.115	-1.282
	(0.771)	(0.398)	**(0.004)**	(0.254)	(0.085)	(0.131)	**(0.032)**	**(0.002)**	**(0.004)**	**(0.003)**	(0.545)	(0.105)
Ave. Linear	1.205	0.708	-0.943	0.528	**-1.864**	-1.282	**-2.291**	**-3.603**	**-2.615**	**-2.320**	1.507	0.400
	(0.881)	(0.758)	(0.177)	(0.699)	**(0.036)**	(0.105)	**(0.015)**	**(0.001)**	**(0.007)**	**(0.014)**	(0.929)	(0.654)
Ave. Local	0.234	-0.669	**-2.481**	-0.610	-1.489	-1.288	**-2.044**	**-3.387**	**-3.277**	**-3.383**	-0.248	-1.221
	(0.592)	(0.254)	**(0.009)**	(0.273)	(0.073)	(0.104)	**(0.025)**	**(0.001)**	**(0.001)**	**(0.001)**	(0.403)	(0.116)
Ave. Non-linear	0.500	0.116	-1.580	-0.192	**-2.241**	**-1.752**	**-3.209**	**-3.425**	**-2.804**	**-2.623**	0.456	-0.666
	(0.690)	(0.546)	(0.062)	(0.425)	**(0.016)**	**(0.045)**	**(0.002)**	**(0.001)**	**(0.004)**	**(0.007)**	(0.674)	(0.255)
Ave. AR+	0.323	-0.300	**-2.159**	-0.630	**-1.775**	-1.555	**-2.475**	**-3.972**	**-3.640**	**-3.755**	-0.265	-1.602
	(0.626)	(0.383)	**(0.019)**	(0.267)	**(0.043)**	(0.065)	**(0.010)**	**(0.000)**	**(0.001)**	**(0.000)**	(0.396)	(0.060)
Tot. Ave.	0.267	-0.238	**-2.084**	-0.629	**-2.164**	**-1.928**	**-3.175**	**-4.263**	**-3.713**	**-3.550**	-0.200	**-1.714**
	(0.605)	(0.407)	**(0.023)**	(0.267)	**(0.019)**	**(0.032)**	**(0.002)**	**(0.000)**	**(0.000)**	**(0.001)**	(0.421)	**(0.048)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.47: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 1$. $N = 31$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	-0.834	-1.012	-1.277	-1.279	-0.580	-0.393	**-2.107**	-0.591	**-2.089**	-1.291	-0.911	1.023
	(0.205)	(0.160)	(0.106)	(0.105)	(0.283)	(0.349)	**(0.022)**	(0.279)	**(0.023)**	(0.103)	(0.185)	(0.843)
RW	-0.138	-0.517	-1.036	-1.106	0.187	0.354	-0.565	0.008	**-1.759**	-0.447	-0.762	1.279
	(0.445)	(0.305)	(0.154)	(0.139)	(0.574)	(0.637)	(0.288)	(0.503)	**(0.044)**	(0.329)	(0.226)	(0.895)
DDD	1.947	1.096	-0.083	-0.360	2.392	2.483	1.680	1.956	0.069	1.664	0.055	2.873
	(0.970)	(0.859)	(0.467)	(0.361)	(0.988)	(0.991)	(0.948)	(0.970)	(0.527)	(0.947)	(0.522)	(0.996)
VAR(4)	0.380	-0.290	-1.033	-1.119	0.359	0.416	-0.092	0.422	-1.352	-0.097	-0.753	1.337
	(0.647)	(0.387)	(0.155)	(0.136)	(0.639)	(0.660)	(0.464)	(0.662)	(0.093)	(0.461)	(0.229)	(0.904)
GETS	1.606	2.127	-0.046	-0.650	1.280	1.321	1.244	1.902	0.141	1.554	0.202	2.027
	(0.941)	(0.979)	(0.482)	(0.260)	(0.895)	(0.902)	(0.888)	(0.967)	(0.556)	(0.935)	(0.579)	(0.974)
GETS-IIS	1.278	1.806	-0.758	-0.964	1.056	1.105	0.961	1.602	-0.254	1.225	-0.220	1.871
	(0.894)	(0.960)	(0.227)	(0.171)	(0.850)	(0.861)	(0.828)	(0.940)	(0.400)	(0.885)	(0.413)	(0.964)
GETS-SIS	2.257	2.136	-0.026	-0.462	1.749	1.844	1.605	2.768	0.188	1.999	0.178	2.890
	(0.984)	(0.980)	(0.490)	(0.324)	(0.955)	(0.962)	(0.941)	(0.995)	(0.574)	(0.973)	(0.570)	(0.996)
GETS-DDD	3.617	3.022	0.867	0.302	2.953	3.065	3.205	4.076	1.106	3.441	0.838	4.202
	(0.999)	(0.997)	(0.803)	(0.618)	(0.997)	(0.998)	(0.998)	(1.000)	(0.861)	(0.999)	(0.796)	(1.000)
GETS-IIS-DDD	3.073	2.308	0.445	0.007	2.860	2.981	2.755	3.423	0.745	2.787	0.505	3.924
	(0.998)	(0.986)	(0.670)	(0.503)	(0.996)	(0.997)	(0.995)	(0.999)	(0.769)	(0.995)	(0.691)	(1.000)
GETS-SIS-DDD	3.042	2.153	0.415	0.007	2.975	3.089	2.767	3.322	0.759	2.722	0.479	4.025
	(0.998)	(0.980)	(0.660)	(0.503)	(0.997)	(0.998)	(0.995)	(0.999)	(0.773)	(0.995)	(0.682)	(1.000)
Ridge, CV	-1.223	-1.132	-1.406	-1.370	-0.089	0.019	-1.029	-0.499	**-2.043**	-1.585	-0.964	1.919
	(0.116)	(0.133)	(0.085)	(0.090)	(0.465)	(0.508)	(0.156)	(0.311)	**(0.025)**	(0.062)	(0.171)	(0.968)
Lasso, CV	2.646	-0.079	-0.992	-1.074	0.780	0.840	0.344	1.441	-1.305	0.455	-0.657	2.555
	(0.994)	(0.469)	(0.165)	(0.146)	(0.779)	(0.796)	(0.633)	(0.920)	(0.101)	(0.674)	(0.258)	(0.992)
ELNET, CV	-	-0.704	-1.256	-1.266	0.221	0.310	-0.497	0.316	**-1.774**	-0.827	-0.858	1.947
	-	(0.244)	(0.109)	(0.108)	(0.587)	(0.621)	(0.311)	(0.623)	**(0.043)**	(0.207)	(0.199)	(0.970)
Ridge, AIC	0.704	-	-1.413	-1.360	0.612	0.682	0.277	1.059	-1.181	0.418	-0.741	1.734
	(0.756)	-	(0.084)	(0.092)	(0.727)	(0.750)	(0.608)	(0.851)	(0.123)	(0.660)	(0.232)	(0.953)
Lasso, AIC	1.256	1.413	-	-1.176	1.085	1.120	0.969	1.429	0.143	1.148	0.355	1.615
	(0.891)	(0.916)	-	(0.124)	(0.857)	(0.864)	(0.830)	(0.918)	(0.556)	(0.870)	(0.638)	(0.942)
ELNET, AIC	1.266	1.360	1.176	-	1.144	1.172	1.043	1.383	0.446	1.179	1.328	1.531
	(0.892)	(0.908)	(0.876)	-	(0.869)	(0.875)	(0.847)	(0.912)	(0.671)	(0.876)	(0.903)	(0.932)
k-NN	-0.221	-0.612	-1.085	-1.144	-	0.656	-0.658	-0.086	**-2.036**	-0.511	-0.787	1.185
	(0.413)	(0.273)	(0.143)	(0.131)	-	(0.741)	(0.258)	(0.466)	**(0.025)**	(0.307)	(0.219)	(0.877)
wk-NN	-0.310	-0.682	-1.120	-1.172	-0.656	-	-0.748	-0.179	**-2.139**	-0.593	-0.815	1.039
	(0.379)	(0.250)	(0.136)	(0.125)	(0.259)	-	(0.230)	(0.430)	**(0.020)**	(0.279)	(0.211)	(0.846)
RF	0.497	-0.277	-0.969	-1.043	0.658	0.748	-	0.706	-1.304	0.009	-0.645	2.530
	(0.689)	(0.392)	(0.170)	(0.153)	(0.742)	(0.770)	-	(0.757)	(0.101)	(0.504)	(0.262)	(0.992)
FFNN	-0.316	-1.059	-1.429	-1.383	0.086	0.179	-0.706	-	**-1.702**	-1.016	-0.953	1.993
	(0.377)	(0.149)	(0.082)	(0.088)	(0.534)	(0.570)	(0.243)	-	**(0.050)**	(0.159)	(0.174)	(0.972)
RNN	1.774	1.181	-0.143	-0.446	2.036	2.139	1.304	1.702	-	1.420	0.018	2.594
	(0.957)	(0.877)	(0.444)	(0.329)	(0.975)	(0.980)	(0.899)	(0.950)	-	(0.917)	(0.507)	(0.993)
SVR-LIN	0.827	-0.418	-1.148	-1.179	0.511	0.593	-0.009	1.016	-1.420	-	-0.730	2.290
	(0.793)	(0.340)	(0.130)	(0.124)	(0.693)	(0.721)	(0.496)	(0.841)	(0.083)	-	(0.236)	(0.985)
SVR-POLY	0.858	0.741	-0.355	-1.328	0.787	0.815	0.645	0.953	-0.018	0.730	-	1.159
	(0.801)	(0.768)	(0.362)	(0.097)	(0.781)	(0.789)	(0.738)	(0.826)	(0.493)	(0.764)	-	(0.872)
SVR-RBF	**-1.947**	**-1.734**	-1.615	-1.531	-1.185	-1.039	**-2.530**	**-1.993**	**-2.594**	**-2.290**	-1.159	-
	(0.030)	**(0.047)**	(0.058)	(0.068)	(0.123)	(0.154)	**(0.008)**	**(0.028)**	**(0.007)**	**(0.015)**	(0.128)	-
SVR-ANOVA	1.198	1.184	0.547	-0.592	1.058	1.085	0.956	1.321	0.287	1.088	1.611	1.474
	(0.880)	(0.877)	(0.706)	(0.279)	(0.851)	(0.857)	(0.827)	(0.902)	(0.612)	(0.857)	(0.941)	(0.925)
AR+SVR-POLY	0.718	-0.104	-1.271	-1.299	0.604	0.680	0.211	1.068	-1.260	0.297	-0.808	1.842
	(0.761)	(0.459)	(0.107)	(0.102)	(0.725)	(0.749)	(0.583)	(0.853)	(0.109)	(0.616)	(0.213)	(0.962)
AR+SVR-RBF	-0.310	-0.831	-1.233	-1.248	-0.008	0.108	-0.863	-0.137	**-1.861**	-0.834	-0.849	1.727
	(0.379)	(0.206)	(0.114)	(0.111)	(0.497)	(0.543)	(0.197)	(0.446)	**(0.036)**	(0.205)	(0.201)	(0.953)
AR+SVR-ANOVA	-0.907	-0.954	-1.285	-1.296	-0.497	-0.372	-1.174	-0.583	**-2.265**	-1.183	-0.953	0.732
	(0.186)	(0.174)	(0.104)	(0.102)	(0.311)	(0.356)	(0.125)	(0.282)	**(0.015)**	(0.123)	(0.174)	(0.765)
AR+FFNN	0.458	-0.271	-0.982	-1.051	0.513	0.600	0.051	0.632	-1.226	0.070	-0.626	1.891
	(0.675)	(0.394)	(0.167)	(0.151)	(0.694)	(0.724)	(0.520)	(0.734)	(0.115)	(0.528)	(0.268)	(0.966)
AR+RNN	1.902	1.055	-0.415	-0.648	2.014	2.157	1.545	2.128	-0.414	1.479	-0.189	3.394
	(0.967)	(0.850)	(0.341)	(0.261)	(0.973)	(0.980)	(0.934)	(0.979)	(0.341)	(0.925)	(0.426)	(0.999)
Ave. BM	-0.378	-0.677	-1.158	-1.198	-0.012	0.121	-0.883	-0.131	**-1.838**	-0.744	-0.843	1.492
	(0.354)	(0.252)	(0.128)	(0.120)	(0.495)	(0.548)	(0.192)	(0.448)	**(0.038)**	(0.231)	(0.203)	(0.927)
Ave. Linear	1.076	0.617	-1.222	-1.229	0.786	0.851	0.531	1.652	-0.882	0.772	-0.651	1.972
	(0.855)	(0.729)	(0.116)	(0.114)	(0.781)	(0.799)	(0.700)	(0.946)	(0.192)	(0.777)	(0.260)	(0.971)
Ave. Local	-0.574	-0.889	-1.226	-1.246	-0.890	-0.506	-1.390	-0.414	**-2.158**	-0.902	-0.882	1.123
	(0.285)	(0.190)	(0.115)	(0.111)	(0.190)	(0.308)	(0.087)	(0.341)	**(0.020)**	(0.187)	(0.192)	(0.865)
Ave. Non-linear	0.048	-1.006	**-1.779**	-1.618	0.184	0.252	-0.256	0.267	-1.658	-0.360	-1.129	1.190
	(0.519)	(0.161)	**(0.043)**	(0.058)	(0.572)	(0.599)	(0.400)	(0.604)	(0.054)	(0.361)	(0.134)	(0.878)
Ave. AR+	-0.783	-1.162	-1.388	-1.359	-0.195	-0.080	-1.181	-0.547	**-2.088**	-1.491	-0.955	1.925
	(0.220)	(0.127)	(0.088)	(0.092)	(0.423)	(0.469)	(0.123)	(0.294)	**(0.023)**	(0.073)	(0.174)	(0.968)
Tot. Ave.	-0.798	-1.658	-1.620	-1.515	-0.145	-0.048	-0.951	-0.963	**-2.008**	-1.538	-1.074	1.370
	(0.216)	(0.054)	(0.058)	(0.070)	(0.443)	(0.481)	(0.175)	(0.172)	**(0.027)**	(0.067)	(0.146)	(0.910)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.48: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 1$. $N = 31$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.211	-0.980	-0.553	0.073	-1.222	**-2.714**	-0.751	-1.205	-0.234	-0.500	-0.323	-0.267
	(0.118)	(0.167)	(0.292)	(0.529)	(0.116)	**(0.005)**	(0.229)	(0.119)	(0.408)	(0.310)	(0.374)	(0.395)
RW	-1.039	-0.540	0.112	0.645	-0.434	**-1.907**	0.262	-0.708	0.669	-0.116	0.300	0.238
	(0.153)	(0.297)	(0.544)	(0.738)	(0.334)	**(0.033)**	(0.602)	(0.242)	(0.746)	(0.454)	(0.617)	(0.593)
DDD	-0.235	1.308	1.954	2.365	1.444	0.521	2.804	0.943	2.481	1.580	2.159	2.084
	(0.408)	(0.900)	(0.970)	(0.988)	(0.920)	(0.697)	(0.996)	(0.823)	(0.991)	(0.938)	(0.981)	(0.977)
VAR(4)	-1.078	-0.299	0.404	0.911	-0.099	-1.192	0.671	-0.528	0.610	0.192	0.630	0.629
	(0.145)	(0.383)	(0.656)	(0.815)	(0.461)	(0.121)	(0.746)	(0.301)	(0.727)	(0.575)	(0.733)	(0.733)
GETS	-0.349	1.550	1.548	1.535	1.317	0.488	1.407	1.864	1.489	2.241	1.775	2.164
	(0.365)	(0.934)	(0.934)	(0.932)	(0.901)	(0.686)	(0.915)	(0.964)	(0.927)	(0.984)	(0.957)	(0.981)
GETS-IIS	-0.724	1.079	1.324	1.311	1.035	0.043	1.142	1.282	1.288	1.752	1.555	1.928
	(0.237)	(0.855)	(0.902)	(0.900)	(0.846)	(0.517)	(0.869)	(0.895)	(0.896)	(0.955)	(0.935)	(0.968)
GETS-SIS	-0.274	2.228	2.069	2.177	1.540	0.649	1.930	2.291	2.044	3.209	2.475	3.175
	(0.393)	(0.983)	(0.976)	(0.981)	(0.933)	(0.739)	(0.968)	(0.985)	(0.975)	(0.998)	(0.990)	(0.998)
GETS-DDD	0.522	3.099	3.552	3.534	3.206	2.062	3.184	3.603	3.387	3.425	3.972	4.263
	(0.697)	(0.998)	(0.999)	(0.999)	(0.998)	(0.976)	(0.998)	(0.999)	(0.999)	(0.999)	(1.000)	(1.000)
GETS-IIS-DDD	0.188	2.561	3.266	3.357	2.616	1.538	2.888	2.615	3.277	2.804	3.640	3.713
	(0.574)	(0.992)	(0.999)	(0.999)	(0.993)	(0.933)	(0.996)	(0.993)	(0.999)	(0.996)	(0.999)	(1.000)
GETS-SIS-DDD	0.177	2.466	3.476	3.583	2.711	1.453	2.929	2.320	3.383	2.623	3.755	3.550
	(0.570)	(0.990)	(0.999)	(0.999)	(0.995)	(0.922)	(0.997)	(0.986)	(0.999)	(0.993)	(1.000)	(0.999)
Ridge, CV	-1.301	-1.175	-0.127	0.516	-0.908	**-2.459**	-0.115	-1.507	0.248	-0.456	0.265	0.200
	(0.102)	(0.125)	(0.450)	(0.695)	(0.186)	**(0.010)**	(0.455)	(0.071)	(0.597)	(0.326)	(0.604)	(0.579)
Lasso, CV	-0.995	0.001	0.986	1.605	0.221	-1.290	1.282	-0.400	1.221	0.666	1.602	1.714
	(0.164)	(0.500)	(0.834)	(0.941)	(0.587)	(0.103)	(0.895)	(0.346)	(0.884)	(0.745)	(0.940)	(0.952)
ELNET, CV	-1.198	-0.718	0.310	0.907	-0.458	**-1.902**	0.378	-1.076	0.574	-0.048	0.783	0.798
	(0.120)	(0.239)	(0.621)	(0.814)	(0.325)	**(0.033)**	(0.646)	(0.145)	(0.715)	(0.481)	(0.780)	(0.784)
Ridge, AIC	-1.184	0.104	0.831	0.954	0.271	-1.055	0.677	-0.617	0.889	1.006	1.162	1.658
	(0.123)	(0.541)	(0.794)	(0.826)	(0.606)	(0.150)	(0.748)	(0.271)	(0.810)	(0.839)	(0.873)	(0.946)
Lasso, AIC	-0.547	1.271	1.233	1.285	0.982	0.415	1.158	1.222	1.226	1.779	1.388	1.620
	(0.294)	(0.893)	(0.886)	(0.896)	(0.833)	(0.659)	(0.872)	(0.884)	(0.885)	(0.957)	(0.912)	(0.942)
ELNET, AIC	0.592	1.299	1.248	1.296	1.051	0.648	1.198	1.229	1.246	1.618	1.359	1.515
	(0.721)	(0.898)	(0.889)	(0.898)	(0.849)	(0.739)	(0.880)	(0.886)	(0.889)	(0.942)	(0.908)	(0.930)
k-NN	-1.058	-0.604	0.008	0.497	-0.513	**-2.014**	0.012	-0.786	0.890	-0.184	0.195	0.145
	(0.149)	(0.275)	(0.503)	(0.689)	(0.306)	**(0.027)**	(0.505)	(0.219)	(0.810)	(0.428)	(0.577)	(0.557)
wk-NN	-1.085	-0.680	-0.108	0.372	-0.600	**-2.157**	-0.121	-0.851	0.506	-0.252	0.080	0.048
	(0.143)	(0.251)	(0.457)	(0.644)	(0.276)	**(0.020)**	(0.452)	(0.201)	(0.692)	(0.401)	(0.531)	(0.519)
RF	-0.956	-0.211	0.863	1.174	-0.051	-1.545	0.883	-0.531	1.390	0.256	1.181	0.951
	(0.173)	(0.417)	(0.803)	(0.875)	(0.480)	(0.066)	(0.808)	(0.300)	(0.913)	(0.600)	(0.877)	(0.825)
FFNN	-1.321	-1.068	0.137	0.583	-0.632	**-2.128**	0.131	-1.652	0.414	-0.267	0.547	0.963
	(0.098)	(0.147)	(0.554)	(0.718)	(0.266)	**(0.021)**	(0.552)	(0.054)	(0.659)	(0.396)	(0.706)	(0.828)
RNN	-0.287	1.260	1.861	2.265	1.226	0.414	1.838	0.882	2.158	1.658	2.088	2.008
	(0.388)	(0.891)	(0.964)	(0.985)	(0.885)	(0.659)	(0.962)	(0.808)	(0.980)	(0.946)	(0.977)	(0.973)
SVR-LIN	-1.088	-0.297	0.834	1.183	-0.070	-1.479	0.744	-0.772	0.902	0.360	1.491	1.538
	(0.143)	(0.384)	(0.795)	(0.877)	(0.472)	(0.075)	(0.769)	(0.223)	(0.813)	(0.639)	(0.927)	(0.933)
SVR-POLY	-1.611	0.808	0.849	0.953	0.626	0.189	0.843	0.651	0.882	1.129	0.955	1.074
	(0.059)	(0.787)	(0.799)	(0.826)	(0.732)	(0.574)	(0.797)	(0.740)	(0.808)	(0.866)	(0.826)	(0.854)
SVR-RBF	-1.474	**-1.842**	**-1.727**	-0.732	**-1.891**	**-3.394**	-1.492	**-1.972**	-1.123	-1.190	**-1.925**	-1.370
	(0.075)	**(0.038)**	**(0.047)**	(0.235)	**(0.034)**	**(0.001)**	(0.073)	**(0.029)**	(0.135)	(0.122)	**(0.032)**	(0.090)
SVR-ANOVA	-	1.216	1.155	1.237	0.940	0.514	1.145	1.108	1.166	1.576	1.280	1.450
	-	(0.883)	(0.871)	(0.887)	(0.823)	(0.694)	(0.869)	(0.862)	(0.874)	(0.937)	(0.895)	(0.921)
AR+SVR-POLY	-1.216	-	0.913	1.199	0.178	-1.097	0.739	-0.563	0.884	1.148	1.291	1.661
	(0.117)	-	(0.816)	(0.880)	(0.570)	(0.141)	(0.767)	(0.289)	(0.808)	(0.870)	(0.897)	(0.946)
AR+SVR-RBF	-1.155	-0.913	-	0.747	-1.018	**-2.026**	0.002	-1.071	0.382	-0.242	0.501	0.211
	(0.129)	(0.184)	-	(0.769)	(0.158)	**(0.026)**	(0.501)	(0.146)	(0.648)	(0.405)	(0.690)	(0.583)
AR+SVR-ANOVA	-1.237	-1.199	-0.747	-	-1.084	**-2.224**	-0.607	-1.191	-0.199	-0.558	-0.455	-0.305
	(0.113)	(0.120)	(0.231)	-	(0.144)	**(0.017)**	(0.274)	(0.121)	(0.422)	(0.291)	(0.326)	(0.381)
AR+FFNN	-0.940	-0.178	1.018	1.084	-	-1.272	0.608	-0.518	0.900	0.268	1.256	0.902
	(0.177)	(0.430)	(0.842)	(0.856)	-	(0.107)	(0.726)	(0.304)	(0.812)	(0.605)	(0.891)	(0.813)
AR+RNN	-0.514	1.097	2.026	2.224	1.272	-	2.137	0.755	2.566	1.631	2.516	2.467
	(0.306)	(0.859)	(0.974)	(0.983)	(0.893)	-	(0.980)	(0.772)	(0.992)	(0.943)	(0.991)	(0.990)
Ave. BM	-1.145	-0.739	-0.002	0.607	-0.608	**-2.137**	-	-0.907	0.419	-0.232	0.229	0.175
	(0.131)	(0.233)	(0.499)	(0.726)	(0.274)	**(0.020)**	-	(0.186)	(0.661)	(0.409)	(0.590)	(0.569)
Ave. Linear	-1.108	0.563	1.071	1.191	0.518	-0.755	0.907	-	1.077	1.758	1.475	2.336
	(0.138)	(0.711)	(0.854)	(0.879)	(0.696)	(0.228)	(0.814)	-	(0.855)	(0.956)	(0.925)	(0.987)
Ave. Local	-1.166	-0.884	-0.382	0.199	-0.900	**-2.566**	-0.419	-1.077	-	-0.407	-0.143	-0.134
	(0.126)	(0.192)	(0.352)	(0.578)	(0.188)	**(0.008)**	(0.339)	(0.145)	-	(0.343)	(0.444)	(0.447)
Ave. Non-linear	-1.576	-1.148	0.242	0.558	-0.268	-1.631	0.232	**-1.758**	0.407	-	0.490	0.783
	(0.063)	(0.130)	(0.595)	(0.709)	(0.395)	(0.057)	(0.591)	**(0.044)**	(0.657)	-	(0.686)	(0.780)
Ave. AR+	-1.280	-1.291	-0.501	0.455	-1.256	**-2.516**	-0.229	-1.475	0.143	-0.490	-	-0.043
	(0.105)	(0.103)	(0.310)	(0.674)	(0.109)	**(0.009)**	(0.410)	(0.075)	(0.556)	(0.314)	-	(0.483)
Tot. Ave.	-1.450	-1.661	-0.211	0.305	-0.902	**-2.467**	-0.175	**-2.336**	0.134	-0.783	0.043	-
	(0.079)	(0.054)	(0.417)	(0.619)	(0.187)	**(0.010)**	(0.431)	**(0.013)**	(0.553)	(0.220)	(0.517)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.49: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 2$. $N = 30$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.367	-0.692	-0.476	-1.472	-1.411	-1.226	**-2.988**	**-2.515**	**-2.422**	-1.529	**-2.734**
	-	(0.358)	(0.247)	(0.319)	(0.076)	(0.084)	(0.115)	**(0.003)**	**(0.009)**	**(0.011)**	(0.069)	**(0.005)**
RW	0.367	-	-1.441	-0.160	-1.576	-1.526	-1.295	**-2.114**	**-1.758**	**-1.912**	**-2.072**	-1.686
	(0.642)	-	(0.080)	(0.437)	(0.063)	(0.069)	(0.103)	**(0.022)**	**(0.045)**	**(0.033)**	**(0.024)**	(0.051)
DDD	0.692	1.441	-	0.319	-1.414	-1.345	-1.151	-1.548	-1.259	-1.405	-0.850	-0.836
	(0.753)	(0.920)	-	(0.624)	(0.084)	(0.095)	(0.130)	(0.066)	(0.109)	(0.085)	(0.201)	(0.205)
VAR(4)	0.476	0.160	-0.319	-	-1.314	-1.245	-1.067	-1.567	-1.309	-1.374	-0.821	-1.008
	(0.681)	(0.563)	(0.376)	-	(0.100)	(0.112)	(0.147)	(0.064)	(0.100)	(0.090)	(0.209)	(0.161)
GETS	1.472	1.576	1.414	1.314	-	1.846	0.455	0.504	0.669	0.593	1.385	1.102
	(0.924)	(0.937)	(0.916)	(0.900)	-	(0.962)	(0.674)	(0.691)	(0.745)	(0.721)	(0.912)	(0.860)
GETS-IIS	1.411	1.526	1.345	1.245	**-1.846**	-	-0.161	0.331	0.514	0.428	1.296	0.984
	(0.916)	(0.931)	(0.905)	(0.888)	**(0.038)**	-	(0.436)	(0.629)	(0.694)	(0.664)	(0.897)	(0.833)
GETS-SIS	1.226	1.295	1.151	1.067	-0.455	0.161	-	0.325	0.477	0.406	1.046	0.844
	(0.885)	(0.897)	(0.870)	(0.853)	(0.326)	(0.564)	-	(0.626)	(0.682)	(0.656)	(0.848)	(0.797)
GETS-DDD	2.988	2.114	1.548	1.567	-0.504	-0.331	-0.325	-	2.591	0.673	1.629	1.580
	(0.997)	(0.978)	(0.934)	(0.936)	(0.309)	(0.371)	(0.374)	-	(0.993)	(0.747)	(0.943)	(0.938)
GETS-IIS-DDD	2.515	1.758	1.259	1.309	-0.669	-0.514	-0.477	**-2.591**	-	-0.939	1.236	1.190
	(0.991)	(0.955)	(0.891)	(0.900)	(0.255)	(0.306)	(0.318)	**(0.007)**	-	(0.178)	(0.887)	(0.878)
GETS-SIS-DDD	2.422	1.912	1.405	1.374	-0.593	-0.428	-0.406	-0.673	0.939	-	1.335	1.247
	(0.989)	(0.967)	(0.915)	(0.910)	(0.279)	(0.336)	(0.344)	(0.253)	(0.822)	-	(0.904)	(0.889)
Ridge, CV	1.529	2.072	0.850	0.821	-1.385	-1.296	-1.046	-1.629	-1.236	-1.335	-	-0.590
	(0.931)	(0.976)	(0.799)	(0.791)	(0.088)	(0.103)	(0.152)	(0.057)	(0.113)	(0.096)	-	(0.280)
Lasso, CV	2.734	1.686	0.836	1.008	-1.102	-0.984	-0.844	-1.580	-1.190	-1.247	0.590	-
	(0.995)	(0.949)	(0.795)	(0.839)	(0.140)	(0.167)	(0.203)	(0.062)	(0.122)	(0.111)	(0.720)	-
ELNET, CV	1.385	1.566	1.400	1.154	-0.914	-0.521	-0.379	0.111	0.289	0.189	1.244	0.919
	(0.912)	(0.936)	(0.914)	(0.871)	(0.184)	(0.303)	(0.354)	(0.544)	(0.613)	(0.574)	(0.888)	(0.817)
Ridge, AIC	1.656	2.149	1.311	1.057	-1.256	-1.142	-0.914	-1.120	-0.789	-0.904	1.239	0.277
	(0.946)	(0.980)	(0.900)	(0.850)	(0.110)	(0.131)	(0.184)	(0.136)	(0.218)	(0.187)	(0.887)	(0.608)
Lasso, AIC	1.727	1.869	1.770	1.587	1.142	1.606	0.973	0.820	0.949	0.876	1.749	1.448
	(0.953)	(0.964)	(0.956)	(0.938)	(0.869)	(0.940)	(0.831)	(0.791)	(0.825)	(0.806)	(0.955)	(0.921)
ELNET, AIC	1.760	1.901	1.817	1.645	1.638	1.913	1.419	0.965	1.082	1.019	1.793	1.518
	(0.956)	(0.966)	(0.960)	(0.945)	(0.944)	(0.967)	(0.917)	(0.829)	(0.856)	(0.842)	(0.958)	(0.930)
k-NN	1.756	1.025	0.633	0.863	-0.994	-0.855	-0.743	-0.989	-0.687	-0.770	0.559	0.267
	(0.955)	(0.843)	(0.734)	(0.802)	(0.164)	(0.200)	(0.232)	(0.165)	(0.249)	(0.224)	(0.710)	(0.604)
wk-NN	2.354	1.711	1.141	1.557	-0.945	-0.816	-0.722	-1.215	-0.841	-0.970	1.133	0.461
	(0.987)	(0.951)	(0.868)	(0.935)	(0.176)	(0.210)	(0.238)	(0.117)	(0.204)	(0.170)	(0.867)	(0.676)
RF	1.331	0.058	-0.336	-0.106	-1.349	-1.272	-1.100	**-2.341**	**-1.934**	**-1.900**	-1.102	**-1.829**
	(0.903)	(0.523)	(0.370)	(0.458)	(0.094)	(0.107)	(0.140)	**(0.013)**	**(0.031)**	**(0.034)**	(0.140)	**(0.039)**
FFNN	1.312	0.217	-0.332	0.002	-1.352	-1.278	-1.090	**-2.134**	**-1.774**	**-1.770**	-1.046	**-4.679**
	(0.900)	(0.585)	(0.371)	(0.501)	(0.093)	(0.106)	(0.142)	**(0.021)**	**(0.043)**	**(0.044)**	(0.152)	**(0.000)**
RNN	4.731	0.941	0.292	0.532	-1.111	-1.021	-0.911	**-2.086**	-1.608	-1.643	-0.176	-0.651
	(1.000)	(0.823)	(0.614)	(0.701)	(0.138)	(0.158)	(0.185)	**(0.023)**	(0.059)	(0.056)	(0.431)	(0.260)
SVR-LIN	1.095	1.170	1.063	0.958	-0.300	0.019	-0.056	0.242	0.364	0.301	0.936	0.742
	(0.859)	(0.874)	(0.852)	(0.827)	(0.383)	(0.508)	(0.478)	(0.595)	(0.641)	(0.617)	(0.821)	(0.768)
SVR-POLY	1.321	1.362	-0.071	0.387	-1.367	-1.294	-1.116	**-2.312**	**-1.882**	**-2.011**	-1.122	-1.183
	(0.902)	(0.908)	(0.472)	(0.649)	(0.091)	(0.103)	(0.137)	**(0.014)**	**(0.035)**	**(0.027)**	(0.136)	(0.123)
SVR-RBF	0.880	-0.038	-0.500	-0.211	-1.383	-1.311	-1.139	**-2.295**	**-1.905**	**-1.915**	-1.290	**-2.017**
	(0.807)	(0.485)	(0.310)	(0.417)	(0.089)	(0.100)	(0.132)	**(0.015)**	**(0.033)**	**(0.033)**	(0.104)	**(0.027)**
SVR-ANOVA	1.483	1.553	1.415	1.564	-0.207	-0.016	-0.062	0.336	0.552	0.457	1.158	0.938
	(0.926)	(0.934)	(0.916)	(0.936)	(0.419)	(0.494)	(0.475)	(0.631)	(0.707)	(0.675)	(0.872)	(0.822)
AR+SVR-POLY	-0.158	-0.687	-1.092	-0.742	-1.586	-1.531	-1.320	**-2.167**	**-1.852**	**-1.887**	**-1.885**	**-2.339**
	(0.438)	(0.249)	(0.142)	(0.232)	(0.062)	(0.068)	(0.099)	**(0.019)**	**(0.037)**	**(0.035)**	**(0.035)**	**(0.013)**
AR+SVR-RBF	0.140	-0.270	-0.670	-0.442	-1.458	-1.389	-1.215	**-1.997**	-1.698	**-1.719**	-1.342	**-1.877**
	(0.555)	(0.394)	(0.254)	(0.331)	(0.078)	(0.088)	(0.117)	**(0.028)**	(0.050)	**(0.048)**	(0.095)	**(0.035)**
AR+SVR-ANOVA	1.352	1.419	0.853	0.907	-1.319	-1.223	-1.019	-1.271	-0.949	-1.104	0.420	0.076
	(0.907)	(0.917)	(0.800)	(0.814)	(0.099)	(0.116)	(0.158)	(0.107)	(0.175)	(0.139)	(0.661)	(0.530)
AR+FFNN	0.405	-0.364	-1.017	-0.371	-1.474	-1.413	-1.197	**-2.161**	**-1.817**	**-1.833**	-1.666	**-4.919**
	(0.656)	(0.359)	(0.159)	(0.357)	(0.076)	(0.084)	(0.121)	**(0.020)**	**(0.040)**	**(0.039)**	(0.053)	**(0.000)**
AR+RNN	1.717	1.016	0.792	0.614	-1.197	-1.112	-0.954	-1.534	-1.199	-1.304	-0.132	-0.920
	(0.952)	(0.841)	(0.783)	(0.728)	(0.120)	(0.138)	(0.174)	(0.068)	(0.120)	(0.101)	(0.448)	(0.183)
Ave. BM	-0.333	-1.298	-1.689	-1.103	-1.624	-1.583	-1.356	**-2.494**	**-2.141**	**-2.202**	**-2.351**	**-2.597**
	(0.371)	(0.102)	(0.051)	(0.140)	(0.058)	(0.062)	(0.093)	**(0.009)**	**(0.020)**	**(0.018)**	**(0.013)**	**(0.007)**
Ave. Linear	1.479	1.740	1.203	0.954	-1.442	-1.330	-0.971	-0.947	-0.592	-0.753	1.106	0.507
	(0.925)	(0.954)	(0.881)	(0.826)	(0.080)	(0.097)	(0.170)	(0.176)	(0.279)	(0.229)	(0.861)	(0.692)
Ave. Local	1.728	0.488	0.033	0.335	-1.255	-1.156	-1.001	**-2.020**	-1.632	-1.631	-0.654	-1.422
	(0.953)	(0.685)	(0.513)	(0.630)	(0.110)	(0.129)	(0.162)	**(0.026)**	(0.057)	(0.057)	(0.259)	(0.083)
Ave. Non-linear	0.135	-0.441	-0.816	-0.374	-1.600	-1.541	-1.312	**-2.841**	**-2.355**	**-2.354**	**-1.927**	**-3.339**
	(0.553)	(0.331)	(0.211)	(0.356)	(0.060)	(0.067)	(0.100)	**(0.004)**	**(0.013)**	**(0.013)**	**(0.032)**	**(0.001)**
Ave. AR+	0.084	-0.543	-0.996	-0.480	-1.559	-1.499	-1.284	**-2.223**	**-1.879**	**-1.909**	**-1.884**	**-2.851**
	(0.533)	(0.296)	(0.164)	(0.317)	(0.065)	(0.072)	(0.105)	**(0.017)**	**(0.035)**	**(0.033)**	**(0.035)**	**(0.004)**
Tot. Ave.	0.399	-0.236	-0.787	-0.268	-1.655	-1.601	-1.332	**-2.681**	**-2.219**	**-2.240**	**-2.629**	**-4.397**
	(0.654)	(0.407)	(0.219)	(0.395)	(0.054)	(0.060)	(0.097)	**(0.006)**	**(0.017)**	**(0.016)**	**(0.007)**	**(0.000)**

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.50: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 2$. $N = 30$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	-1.385	-1.656	**-1.727**	**-1.760**	**-1.756**	**-2.354**	-1.331	-1.312	**-4.731**	-1.095	-1.321	-0.880
	(0.088)	(0.054)	**(0.047)**	**(0.044)**	**(0.045)**	**(0.013)**	(0.097)	(0.100)	**(0.000)**	(0.141)	(0.098)	(0.193)
RW	-1.566	**-2.149**	**-1.869**	**-1.901**	-1.025	**-1.711**	-0.058	-0.217	-0.941	-1.170	-1.362	0.038
	(0.064)	**(0.020)**	**(0.036)**	**(0.034)**	(0.157)	**(0.049)**	(0.477)	(0.415)	(0.177)	(0.126)	(0.092)	(0.515)
DDD	-1.400	-1.311	**-1.770**	**-1.817**	-0.633	-1.141	0.336	0.332	-0.292	-1.063	0.071	0.500
	(0.086)	(0.100)	**(0.044)**	**(0.040)**	(0.266)	(0.132)	(0.630)	(0.629)	(0.386)	(0.148)	(0.528)	(0.690)
VAR(4)	-1.154	-1.057	-1.587	-1.645	-0.863	-1.557	0.106	-0.002	-0.532	-0.958	-0.387	0.211
	(0.129)	(0.150)	(0.062)	(0.055)	(0.198)	(0.065)	(0.542)	(0.499)	(0.299)	(0.173)	(0.351)	(0.583)
GETS	0.914	1.256	-1.142	-1.638	0.994	0.945	1.349	1.352	1.111	0.300	1.367	1.383
	(0.816)	(0.890)	(0.131)	(0.056)	(0.836)	(0.824)	(0.906)	(0.907)	(0.862)	(0.617)	(0.909)	(0.911)
GETS-IIS	0.521	1.142	-1.606	**-1.913**	0.855	0.816	1.272	1.278	1.021	-0.019	1.294	1.311
	(0.697)	(0.869)	(0.060)	**(0.033)**	(0.800)	(0.790)	(0.893)	(0.894)	(0.842)	(0.492)	(0.897)	(0.900)
GETS-SIS	0.379	0.914	-0.973	-1.419	0.743	0.722	1.100	1.090	0.911	0.056	1.116	1.139
	(0.646)	(0.816)	(0.169)	(0.083)	(0.768)	(0.762)	(0.860)	(0.858)	(0.815)	(0.522)	(0.863)	(0.868)
GETS-DDD	-0.111	1.120	-0.820	-0.965	0.989	1.215	2.341	2.134	2.086	-0.242	2.312	2.295
	(0.456)	(0.864)	(0.209)	(0.171)	(0.835)	(0.883)	(0.987)	(0.979)	(0.977)	(0.405)	(0.986)	(0.985)
GETS-IIS-DDD	-0.289	0.789	-0.949	-1.082	0.687	0.841	1.934	1.774	1.608	-0.364	1.882	1.905
	(0.387)	(0.782)	(0.175)	(0.144)	(0.751)	(0.796)	(0.969)	(0.957)	(0.941)	(0.359)	(0.965)	(0.967)
GETS-SIS-DDD	-0.189	0.904	-0.876	-1.019	0.770	0.970	1.900	1.770	1.643	-0.301	2.011	1.915
	(0.426)	(0.813)	(0.194)	(0.158)	(0.776)	(0.830)	(0.966)	(0.956)	(0.944)	(0.383)	(0.973)	(0.967)
Ridge, CV	-1.244	-1.239	**-1.749**	**-1.793**	-0.559	-1.133	1.102	1.046	0.176	-0.936	1.122	1.290
	(0.112)	(0.113)	**(0.045)**	**(0.042)**	(0.290)	(0.133)	(0.860)	(0.848)	(0.569)	(0.179)	(0.864)	(0.896)
Lasso, CV	-0.919	-0.277	-1.448	-1.518	-0.267	-0.461	1.829	4.679	0.651	-0.742	1.183	2.017
	(0.183)	(0.392)	(0.079)	(0.070)	(0.396)	(0.324)	(0.961)	(1.000)	(0.740)	(0.232)	(0.877)	(0.973)
ELNET, CV	-	1.055	**-2.441**	**-2.363**	0.866	0.808	1.248	1.226	0.928	-0.473	1.242	1.287
	-	(0.850)	**(0.010)**	**(0.013)**	(0.803)	(0.787)	(0.889)	(0.885)	(0.819)	(0.320)	(0.888)	(0.896)
Ridge, AIC	-1.055	-	-1.656	**-1.721**	-0.056	-0.264	1.279	1.450	0.518	-0.815	1.323	1.468
	(0.150)	-	(0.054)	**(0.048)**	(0.478)	(0.397)	(0.895)	(0.921)	(0.696)	(0.211)	(0.902)	(0.924)
Lasso, AIC	2.441	1.656	-	**-1.724**	1.432	1.383	1.631	1.625	1.369	1.703	1.660	1.660
	(0.990)	(0.946)	-	**(0.048)**	(0.919)	(0.911)	(0.943)	(0.943)	(0.909)	(0.950)	(0.946)	(0.946)
ELNET, AIC	2.363	1.721	1.724	-	1.489	1.452	1.671	1.675	1.437	2.340	1.704	1.702
	(0.987)	(0.952)	(0.952)	-	(0.926)	(0.921)	(0.947)	(0.948)	(0.919)	(0.987)	(0.950)	(0.950)
k-NN	-0.866	0.056	-1.432	-1.489	-	-0.160	1.466	1.645	0.640	-0.697	0.812	1.499
	(0.197)	(0.522)	(0.081)	(0.074)	-	(0.437)	(0.923)	(0.945)	(0.736)	(0.246)	(0.788)	(0.928)
wk-NN	-0.808	0.264	-1.383	-1.452	0.160	-	1.882	2.348	0.928	-0.674	1.318	1.988
	(0.213)	(0.603)	(0.089)	(0.079)	(0.563)	-	(0.965)	(0.987)	(0.819)	(0.253)	(0.901)	(0.972)
RF	-1.248	-1.279	-1.631	-1.671	-1.466	**-1.882**	-	-0.205	-1.549	-0.993	-0.555	0.257
	(0.111)	(0.105)	(0.057)	(0.053)	(0.077)	**(0.035)**	-	(0.419)	(0.066)	(0.164)	(0.292)	(0.600)
FFNN	-1.226	-1.450	-1.625	-1.675	-1.645	**-2.348**	0.205	-	-1.053	-0.984	-0.507	0.421
	(0.115)	(0.079)	(0.057)	(0.052)	(0.055)	**(0.013)**	(0.581)	-	(0.151)	(0.167)	(0.308)	(0.662)
RNN	-0.928	-0.518	-1.369	-1.437	-0.640	-0.928	1.549	1.053	-	-0.794	0.571	1.604
	(0.181)	(0.304)	(0.091)	(0.081)	(0.264)	(0.181)	(0.934)	(0.849)	-	(0.217)	(0.714)	(0.940)
SVR-LIN	0.473	0.815	**-1.703**	**-2.340**	0.697	0.674	0.993	0.984	0.794	-	0.975	1.025
	(0.680)	(0.789)	**(0.050)**	**(0.013)**	(0.754)	(0.747)	(0.836)	(0.833)	(0.783)	-	(0.831)	(0.843)
SVR-POLY	-1.242	-1.323	-1.660	**-1.704**	-0.812	-1.318	0.555	0.507	-0.571	-0.975	-	0.884
	(0.112)	(0.098)	(0.054)	**(0.050)**	(0.212)	(0.099)	(0.708)	(0.692)	(0.286)	(0.169)	-	(0.808)
SVR-RBF	-1.287	-1.468	-1.660	**-1.702**	-1.499	**-1.988**	-0.257	-0.421	-1.604	-1.025	-0.884	-
	(0.104)	(0.076)	(0.054)	**(0.050)**	(0.072)	**(0.028)**	(0.400)	(0.338)	(0.060)	(0.157)	(0.192)	-
SVR-ANOVA	0.171	0.935	-0.557	-0.742	0.743	0.902	1.317	1.299	1.064	-0.021	1.404	1.357
	(0.567)	(0.821)	(0.291)	(0.232)	(0.768)	(0.813)	(0.901)	(0.898)	(0.852)	(0.492)	(0.914)	(0.907)
AR+SVR-POLY	-1.495	**-2.125**	**-1.838**	**-1.871**	-1.639	**-2.020**	-0.725	-0.952	-1.600	-1.164	-1.656	-0.905
	(0.073)	**(0.021)**	**(0.038)**	**(0.036)**	(0.056)	**(0.026)**	(0.237)	(0.174)	(0.060)	(0.127)	(0.054)	(0.187)
AR+SVR-RBF	-1.340	-1.583	**-1.711**	**-1.755**	-1.492	**-1.750**	-0.457	-0.542	-1.312	-1.068	-0.941	-0.456
	(0.095)	(0.062)	**(0.049)**	**(0.045)**	(0.073)	**(0.045)**	(0.326)	(0.296)	(0.100)	(0.147)	(0.177)	(0.326)
AR+SVR-ANOVA	-0.896	-0.081	-1.513	-1.605	-0.089	-0.241	0.991	0.964	0.433	-0.760	1.114	1.144
	(0.189)	(0.468)	(0.071)	(0.060)	(0.465)	(0.406)	(0.835)	(0.828)	(0.666)	(0.227)	(0.863)	(0.869)
AR+FFNN	-1.385	**-1.945**	**-1.751**	**-1.788**	**-2.247**	**-4.113**	-0.467	-1.155	-1.471	-1.093	**-1.915**	-0.411
	(0.088)	**(0.031)**	**(0.045)**	**(0.042)**	**(0.016)**	**(0.000)**	(0.322)	(0.129)	(0.076)	(0.142)	**(0.033)**	(0.342)
AR+RNN	-0.964	-0.599	-1.424	-1.507	-0.503	-0.851	0.957	1.124	0.093	-0.820	2.657	1.633
	(0.171)	(0.277)	(0.083)	(0.071)	(0.309)	(0.201)	(0.827)	(0.865)	(0.537)	(0.209)	(0.994)	(0.943)
Ave. BM	-1.566	**-2.281**	**-1.875**	**-1.904**	-1.520	**-2.619**	-0.854	-1.235	**-1.926**	-1.213	**-9.895**	-1.100
	(0.064)	**(0.015)**	**(0.035)**	**(0.033)**	(0.070)	**(0.007)**	(0.200)	(0.113)	**(0.032)**	(0.117)	**(0.000)**	(0.140)
Ave. Linear	-1.172	0.535	**-1.847**	**-1.901**	0.250	0.141	1.181	1.194	0.645	-0.839	1.202	1.280
	(0.125)	(0.702)	**(0.037)**	**(0.034)**	(0.598)	(0.555)	(0.876)	(0.879)	(0.738)	(0.204)	(0.880)	(0.895)
Ave. Local	-1.179	-1.037	-1.609	-1.647	-1.665	**-1.813**	1.081	0.966	-0.507	-0.920	0.101	1.069
	(0.124)	(0.154)	(0.059)	(0.055)	(0.053)	**(0.040)**	(0.856)	(0.829)	(0.308)	(0.182)	(0.540)	(0.853)
Ave. Non-linear	-1.545	**-2.197**	**-1.872**	**-1.896**	**-2.023**	**-2.206**	-0.594	-1.078	**-2.144**	-1.176	-1.327	-0.553
	(0.067)	**(0.018)**	**(0.036)**	**(0.034)**	**(0.026)**	**(0.018)**	(0.279)	(0.145)	**(0.020)**	(0.125)	(0.097)	(0.292)
Ave. AR+	-1.477	**-2.190**	**-1.823**	**-1.856**	**-1.772**	**-2.094**	-0.560	-0.919	-1.606	-1.142	-1.536	-0.699
	(0.075)	**(0.018)**	**(0.039)**	**(0.037)**	**(0.043)**	**(0.023)**	(0.290)	(0.183)	(0.060)	(0.131)	(0.068)	(0.245)
Tot. Ave.	-1.575	**-2.684**	**-1.927**	**-1.948**	**-1.931**	**-2.653**	-0.283	-0.577	-1.456	-1.178	-1.560	-0.178
	(0.063)	**(0.006)**	**(0.032)**	**(0.031)**	**(0.032)**	**(0.006)**	(0.389)	(0.284)	(0.078)	(0.124)	(0.065)	(0.430)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.51: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 2$. $N = 30$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.483	0.158	-0.140	-1.352	-0.405	**-1.717**	0.333	-1.479	**-1.728**	-0.135	-0.084	-0.399
	(0.074)	(0.562)	(0.445)	(0.093)	(0.344)	**(0.048)**	(0.629)	(0.075)	**(0.047)**	(0.447)	(0.467)	(0.346)
RW	-1.553	0.687	0.270	-1.419	0.364	-1.016	1.298	**-1.740**	-0.488	0.441	0.543	0.236
	(0.066)	(0.751)	(0.606)	(0.083)	(0.641)	(0.159)	(0.898)	**(0.046)**	(0.315)	(0.669)	(0.704)	(0.593)
DDD	-1.415	1.092	0.670	-0.853	1.017	-0.792	1.689	-1.203	-0.033	0.816	0.996	0.787
	(0.084)	(0.858)	(0.746)	(0.200)	(0.841)	(0.217)	(0.949)	(0.119)	(0.487)	(0.789)	(0.836)	(0.781)
VAR(4)	-1.564	0.742	0.442	-0.907	0.371	-0.614	1.103	-0.954	-0.335	0.374	0.480	0.268
	(0.064)	(0.768)	(0.669)	(0.186)	(0.643)	(0.272)	(0.860)	(0.174)	(0.370)	(0.644)	(0.683)	(0.605)
GETS	0.207	1.586	1.458	1.319	1.474	1.197	1.624	1.442	1.255	1.600	1.559	1.655
	(0.581)	(0.938)	(0.922)	(0.901)	(0.924)	(0.880)	(0.942)	(0.920)	(0.890)	(0.940)	(0.935)	(0.946)
GETS-IIS	0.016	1.531	1.389	1.223	1.413	1.112	1.583	1.330	1.156	1.541	1.499	1.601
	(0.506)	(0.932)	(0.912)	(0.884)	(0.916)	(0.862)	(0.938)	(0.903)	(0.871)	(0.933)	(0.928)	(0.940)
GETS-SIS	0.062	1.320	1.215	1.019	1.197	0.954	1.356	0.971	1.001	1.312	1.284	1.332
	(0.525)	(0.901)	(0.883)	(0.842)	(0.879)	(0.826)	(0.907)	(0.830)	(0.838)	(0.900)	(0.895)	(0.903)
GETS-DDD	-0.336	2.167	1.997	1.271	2.161	1.534	2.494	0.947	2.020	2.841	2.223	2.681
	(0.369)	(0.981)	(0.972)	(0.893)	(0.980)	(0.932)	(0.991)	(0.824)	(0.974)	(0.996)	(0.983)	(0.994)
GETS-IIS-DDD	-0.552	1.852	1.698	0.949	1.817	1.199	2.141	0.592	1.632	2.355	1.879	2.219
	(0.293)	(0.963)	(0.950)	(0.825)	(0.960)	(0.880)	(0.980)	(0.721)	(0.943)	(0.987)	(0.965)	(0.983)
GETS-SIS-DDD	-0.457	1.887	1.719	1.104	1.833	1.304	2.202	0.753	1.631	2.354	1.909	2.240
	(0.325)	(0.965)	(0.952)	(0.861)	(0.961)	(0.899)	(0.982)	(0.771)	(0.943)	(0.987)	(0.967)	(0.984)
Ridge, CV	-1.158	1.885	1.342	-0.420	1.666	0.132	2.351	-1.106	0.654	1.927	1.884	2.629
	(0.128)	(0.965)	(0.905)	(0.339)	(0.947)	(0.552)	(0.987)	(0.139)	(0.741)	(0.968)	(0.965)	(0.993)
Lasso, CV	-0.938	2.339	1.877	-0.076	4.919	0.920	2.597	-0.507	1.422	3.339	2.851	4.397
	(0.178)	(0.987)	(0.965)	(0.470)	(1.000)	(0.817)	(0.993)	(0.308)	(0.917)	(0.999)	(0.996)	(1.000)
ELNET, CV	-0.171	1.495	1.340	0.896	1.385	0.964	1.566	1.172	1.179	1.545	1.477	1.575
	(0.433)	(0.927)	(0.905)	(0.811)	(0.912)	(0.829)	(0.936)	(0.875)	(0.876)	(0.933)	(0.925)	(0.937)
Ridge, AIC	-0.935	2.125	1.583	0.081	1.945	0.599	2.281	-0.535	1.037	2.197	2.190	2.684
	(0.179)	(0.979)	(0.938)	(0.532)	(0.969)	(0.723)	(0.985)	(0.298)	(0.846)	(0.982)	(0.982)	(0.994)
Lasso, AIC	0.557	1.838	1.711	1.513	1.751	1.424	1.875	1.847	1.609	1.872	1.823	1.927
	(0.709)	(0.962)	(0.951)	(0.929)	(0.955)	(0.917)	(0.965)	(0.963)	(0.941)	(0.964)	(0.961)	(0.968)
ELNET, AIC	0.742	1.871	1.755	1.605	1.788	1.507	1.904	1.901	1.647	1.896	1.856	1.948
	(0.768)	(0.964)	(0.955)	(0.940)	(0.958)	(0.929)	(0.967)	(0.966)	(0.945)	(0.966)	(0.963)	(0.969)
k-NN	-0.743	1.639	1.492	0.089	2.247	0.503	1.520	-0.250	1.665	2.023	1.772	1.931
	(0.232)	(0.944)	(0.927)	(0.535)	(0.984)	(0.691)	(0.930)	(0.402)	(0.947)	(0.974)	(0.957)	(0.968)
wk-NN	-0.902	2.020	1.750	0.241	4.113	0.851	2.619	-0.141	1.813	2.206	2.094	2.653
	(0.187)	(0.974)	(0.955)	(0.594)	(1.000)	(0.799)	(0.993)	(0.445)	(0.960)	(0.982)	(0.977)	(0.994)
RF	-1.317	0.725	0.457	-0.991	0.467	-0.957	0.854	-1.181	-1.081	0.594	0.560	0.283
	(0.099)	(0.763)	(0.674)	(0.165)	(0.678)	(0.173)	(0.800)	(0.124)	(0.144)	(0.721)	(0.710)	(0.611)
FFNN	-1.299	0.952	0.542	-0.964	1.155	-1.124	1.235	-1.194	-0.966	1.078	0.919	0.577
	(0.102)	(0.826)	(0.704)	(0.172)	(0.871)	(0.135)	(0.887)	(0.121)	(0.171)	(0.855)	(0.817)	(0.716)
RNN	-1.064	1.600	1.312	-0.433	1.471	-0.093	1.926	-0.645	0.507	2.144	1.606	1.456
	(0.148)	(0.940)	(0.900)	(0.334)	(0.924)	(0.463)	(0.968)	(0.262)	(0.692)	(0.980)	(0.940)	(0.922)
SVR-LIN	0.021	1.164	1.068	0.760	1.093	0.820	1.213	0.839	0.920	1.176	1.142	1.178
	(0.508)	(0.873)	(0.853)	(0.773)	(0.858)	(0.791)	(0.883)	(0.796)	(0.818)	(0.875)	(0.869)	(0.876)
SVR-POLY	-1.404	1.656	0.941	-1.114	1.915	**-2.657**	9.895	-1.202	-0.101	1.327	1.536	1.560
	(0.086)	(0.946)	(0.823)	(0.137)	(0.967)	**(0.006)**	(1.000)	(0.120)	(0.460)	(0.903)	(0.932)	(0.935)
SVR-RBF	-1.357	0.905	0.456	-1.144	0.411	-1.633	1.100	-1.280	-1.069	0.553	0.699	0.178
	(0.093)	(0.813)	(0.674)	(0.131)	(0.658)	(0.057)	(0.860)	(0.105)	(0.147)	(0.708)	(0.755)	(0.570)
SVR-ANOVA	-	1.525	1.392	1.205	1.444	1.090	1.764	0.832	1.152	1.430	1.442	1.493
	-	(0.931)	(0.913)	(0.881)	(0.920)	(0.858)	(0.956)	(0.794)	(0.871)	(0.918)	(0.920)	(0.927)
AR+SVR-POLY	-1.525	-	-0.746	-1.683	-0.636	**-2.545**	0.253	-1.619	-1.177	-0.280	-0.769	-0.600
	(0.069)	-	(0.231)	(0.052)	(0.265)	**(0.008)**	(0.599)	(0.058)	(0.124)	(0.391)	(0.224)	(0.277)
AR+SVR-RBF	-1.392	0.746	-	-1.346	-0.130	-1.558	0.519	-1.323	-0.964	0.057	0.131	-0.174
	(0.087)	(0.769)	-	(0.094)	(0.449)	(0.065)	(0.696)	(0.098)	(0.172)	(0.522)	(0.552)	(0.432)
AR+SVR-ANOVA	-1.205	1.683	1.346	-	1.297	0.483	1.853	-0.386	0.678	1.459	1.535	1.630
	(0.119)	(0.948)	(0.906)	-	(0.898)	(0.684)	(0.963)	(0.351)	(0.748)	(0.922)	(0.932)	(0.943)
AR+FFNN	-1.444	0.636	0.130	-1.297	-	-1.639	1.227	-1.453	**-2.541**	0.284	0.394	-0.106
	(0.080)	(0.735)	(0.551)	(0.102)	-	(0.056)	(0.885)	(0.078)	**(0.008)**	(0.611)	(0.652)	(0.458)
AR+RNN	-1.090	2.545	1.558	-0.483	1.639	-	3.655	-0.682	0.434	2.429	2.597	1.964
	(0.142)	(0.992)	(0.935)	(0.316)	(0.944)	-	(0.999)	(0.250)	(0.666)	(0.989)	(0.993)	(0.970)
Ave. BM	**-1.764**	-0.253	-0.519	**-1.853**	-1.227	**-3.655**	-	**-1.765**	-1.252	-0.451	-0.645	-0.840
	(0.044)	(0.401)	(0.304)	**(0.037)**	(0.115)	**(0.001)**	-	**(0.044)**	(0.110)	(0.328)	(0.262)	(0.204)
Ave. Linear	-0.832	1.619	1.323	0.386	1.453	0.682	1.765	-	1.017	1.853	1.629	2.011
	(0.206)	(0.942)	(0.902)	(0.649)	(0.922)	(0.750)	(0.956)	-	(0.841)	(0.963)	(0.943)	(0.973)
Ave. Local	-1.152	1.177	0.964	-0.678	2.541	-0.434	1.252	-1.017	-	1.436	1.204	1.225
	(0.129)	(0.876)	(0.828)	(0.252)	(0.992)	(0.334)	(0.890)	(0.159)	-	(0.919)	(0.881)	(0.885)
Ave. Non-linear	-1.430	0.280	-0.057	-1.459	-0.284	**-2.429**	0.451	**-1.853**	-1.436	-	0.023	-0.594
	(0.082)	(0.609)	(0.478)	(0.078)	(0.389)	**(0.011)**	(0.672)	**(0.037)**	(0.081)	-	(0.509)	(0.279)
Ave. AR+	-1.442	0.769	-0.131	-1.535	-0.394	**-2.597**	0.645	-1.629	-1.204	-0.023	-	-0.425
	(0.080)	(0.776)	(0.448)	(0.068)	(0.348)	**(0.007)**	(0.738)	(0.057)	(0.119)	(0.491)	-	(0.337)
Tot. Ave.	-1.493	0.600	0.174	-1.630	0.106	**-1.964**	0.840	**-2.011**	-1.225	0.594	0.425	-
	(0.073)	(0.723)	(0.568)	(0.057)	(0.542)	**(0.030)**	(0.796)	**(0.027)**	(0.115)	(0.721)	(0.663)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.52: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 3$. $N = 29$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-0.198	-0.192	-0.895	**-2.679**	**-2.808**	**-3.179**	**-2.759**	**-2.865**	**-2.379**	-0.790	-0.145
	-	(0.422)	(0.425)	(0.189)	**(0.006)**	**(0.004)**	**(0.002)**	**(0.005)**	**(0.004)**	**(0.012)**	(0.218)	(0.443)
RW	0.198	-	0.086	-0.449	**-3.169**	**-3.228**	**-3.587**	**-3.500**	**-3.616**	**-2.719**	-0.392	0.098
	(0.578)	-	(0.534)	(0.328)	**(0.002)**	**(0.002)**	**(0.001)**	**(0.001)**	**(0.001)**	**(0.006)**	(0.349)	(0.539)
DDD	0.192	-0.086	-	-0.458	**-3.296**	**-3.353**	**-3.675**	**-3.404**	**-3.498**	**-2.649**	-0.406	0.094
	(0.575)	(0.466)	-	(0.325)	**(0.001)**	**(0.001)**	**(0.000)**	**(0.001)**	**(0.001)**	**(0.007)**	(0.344)	(0.537)
VAR(4)	0.895	0.449	0.458	-	**-2.396**	**-3.093**	**-3.254**	**-2.076**	**-2.027**	-1.600	0.416	1.038
	(0.811)	(0.672)	(0.675)	-	**(0.012)**	**(0.002)**	**(0.001)**	**(0.024)**	**(0.026)**	(0.060)	(0.660)	(0.846)
GETS	2.679	3.169	3.296	2.396	-	-1.058	-1.300	-0.903	-0.754	-0.551	3.684	4.466
	(0.994)	(0.998)	(0.999)	(0.988)	-	(0.150)	(0.102)	(0.187)	(0.229)	(0.293)	(1.000)	(1.000)
GETS-IIS	2.808	3.228	3.353	3.093	1.058	-	-0.687	-0.752	-0.597	-0.414	3.947	4.403
	(0.996)	(0.998)	(0.999)	(0.998)	(0.850)	-	(0.249)	(0.229)	(0.278)	(0.341)	(1.000)	(1.000)
GETS-SIS	3.179	3.587	3.675	3.254	1.300	0.687	-	-0.527	-0.362	-0.216	4.896	5.730
	(0.998)	(0.999)	(1.000)	(0.999)	(0.898)	(0.751)	-	(0.301)	(0.360)	(0.415)	(1.000)	(1.000)
GETS-DDD	2.759	3.500	3.404	2.076	0.903	0.752	0.527	-	2.118	1.059	2.259	2.572
	(0.995)	(0.999)	(0.999)	(0.976)	(0.813)	(0.771)	(0.699)	-	(0.978)	(0.851)	(0.984)	(0.992)
GETS-IIS-DDD	2.865	3.616	3.498	2.027	0.754	0.597	0.362	**-2.118**	-	0.519	2.203	2.529
	(0.996)	(0.999)	(0.999)	(0.974)	(0.771)	(0.722)	(0.640)	**(0.022)**	-	(0.696)	(0.982)	(0.991)
GETS-SIS-DDD	2.379	2.719	2.649	1.600	0.551	0.414	0.216	-1.059	-0.519	-	1.784	2.058
	(0.988)	(0.994)	(0.993)	(0.940)	(0.707)	(0.659)	(0.585)	(0.149)	(0.304)	-	(0.957)	(0.975)
Ridge, CV	0.790	0.392	0.406	-0.416	**-3.684**	**-3.947**	**-4.896**	**-2.259**	**-2.203**	**-1.784**	-	1.910
	(0.782)	(0.651)	(0.656)	(0.340)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.016)**	**(0.018)**	**(0.043)**	-	(0.967)
Lasso, CV	0.145	-0.098	-0.094	-1.038	**-4.466**	**-4.403**	**-5.730**	**-2.572**	**-2.529**	**-2.058**	**-1.910**	-
	(0.557)	(0.461)	(0.463)	(0.154)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.008)**	**(0.009)**	**(0.025)**	**(0.033)**	-
ELNET, CV	0.482	0.220	0.232	-0.550	**-4.473**	**-4.263**	**-5.763**	**-2.379**	**-2.320**	**-1.898**	-0.832	1.628
	(0.683)	(0.586)	(0.591)	(0.293)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.012)**	**(0.014)**	**(0.034)**	(0.206)	(0.943)
Ridge, AIC	1.077	1.114	1.126	0.995	-0.876	-1.373	-1.289	-1.236	-1.090	-0.851	1.035	1.306
	(0.855)	(0.863)	(0.865)	(0.836)	(0.194)	(0.090)	(0.104)	(0.113)	(0.143)	(0.201)	(0.845)	(0.899)
Lasso, AIC	1.715	1.795	1.802	1.810	0.805	0.739	0.376	-0.078	0.041	0.105	1.772	1.920
	(0.951)	(0.958)	(0.959)	(0.959)	(0.786)	(0.767)	(0.645)	(0.469)	(0.516)	(0.541)	(0.956)	(0.967)
ELNET, AIC	1.669	1.736	1.742	1.735	0.853	0.786	0.440	-0.018	0.095	0.151	1.737	1.869
	(0.947)	(0.953)	(0.954)	(0.953)	(0.799)	(0.781)	(0.668)	(0.493)	(0.537)	(0.560)	(0.953)	(0.964)
k-NN	1.037	0.842	0.877	0.726	**-1.948**	**-2.216**	**-2.961**	**-1.921**	**-1.794**	-1.442	1.057	2.205
	(0.846)	(0.797)	(0.806)	(0.763)	**(0.031)**	**(0.018)**	**(0.003)**	**(0.032)**	**(0.042)**	(0.080)	(0.850)	(0.982)
wk-NN	1.343	0.935	0.967	1.166	-1.610	**-1.833**	**-2.569**	-1.701	-1.586	-1.300	1.488	2.598
	(0.905)	(0.821)	(0.829)	(0.873)	(0.059)	**(0.039)**	**(0.008)**	(0.050)	(0.062)	(0.102)	(0.926)	(0.993)
RF	-0.432	-0.405	-0.403	-1.616	**-3.750**	**-3.864**	**-4.529**	**-2.751**	**-2.792**	**-2.286**	**-1.982**	-0.668
	(0.334)	(0.344)	(0.345)	(0.059)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.005)**	**(0.005)**	**(0.015)**	**(0.029)**	(0.255)
FFNN	0.494	0.360	0.372	-0.359	**-5.125**	**-6.059**	**-4.851**	**-2.463**	**-2.360**	**-1.873**	-0.108	0.775
	(0.687)	(0.639)	(0.644)	(0.361)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.010)**	**(0.013)**	**(0.036)**	(0.457)	(0.778)
RNN	2.641	2.570	2.527	1.664	-0.020	-0.280	-0.851	-1.067	-0.937	-0.670	1.961	2.461
	(0.993)	(0.992)	(0.991)	(0.946)	(0.492)	(0.391)	(0.201)	(0.147)	(0.178)	(0.254)	(0.970)	(0.990)
SVR-LIN	1.007	1.055	1.071	0.723	-1.404	**-2.039**	**-1.731**	**-1.841**	**-1.709**	-1.279	0.791	1.167
	(0.839)	(0.850)	(0.853)	(0.762)	(0.086)	**(0.025)**	**(0.047)**	**(0.038)**	**(0.049)**	(0.106)	(0.782)	(0.874)
SVR-POLY	0.414	0.142	0.150	-0.734	**-4.197**	**-4.601**	**-4.770**	**-2.305**	**-2.259**	**-1.831**	-0.491	0.340
	(0.659)	(0.556)	(0.559)	(0.234)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.014)**	**(0.016)**	**(0.039)**	(0.314)	(0.632)
SVR-RBF	-0.768	-1.077	-1.079	-1.373	**-4.789**	**-4.321**	**-5.721**	**-3.040**	**-3.064**	**-2.538**	**-1.867**	-1.382
	(0.224)	(0.145)	(0.145)	(0.090)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.003)**	**(0.002)**	**(0.008)**	**(0.036)**	(0.089)
SVR-ANOVA	1.064	0.931	0.960	0.754	-1.241	-1.577	**-1.842**	**-2.054**	**-1.946**	-1.464	0.767	1.179
	(0.852)	(0.820)	(0.827)	(0.772)	(0.113)	(0.063)	**(0.038)**	**(0.025)**	**(0.031)**	(0.077)	(0.775)	(0.876)
AR+SVR-POLY	0.780	0.217	0.231	-0.578	**-3.088**	**-3.238**	**-3.987**	**-2.546**	**-2.536**	**-2.091**	-0.481	0.545
	(0.779)	(0.585)	(0.591)	(0.284)	**(0.002)**	**(0.002)**	**(0.000)**	**(0.008)**	**(0.009)**	**(0.023)**	(0.317)	(0.705)
AR+SVR-RBF	0.951	0.182	0.190	-0.431	**-2.631**	**-2.722**	**-3.081**	**-2.571**	**-2.617**	**-2.184**	-0.326	0.376
	(0.825)	(0.572)	(0.575)	(0.335)	**(0.007)**	**(0.006)**	**(0.002)**	**(0.008)**	**(0.007)**	**(0.019)**	(0.373)	(0.645)
AR+SVR-ANOVA	0.885	0.431	0.447	-0.350	**-2.920**	**-3.467**	**-3.716**	**-2.334**	**-2.309**	**-1.827**	0.053	1.033
	(0.808)	(0.665)	(0.671)	(0.365)	**(0.003)**	**(0.001)**	**(0.000)**	**(0.014)**	**(0.014)**	**(0.039)**	(0.521)	(0.845)
AR+FFNN	0.733	0.555	0.577	-0.056	**-3.183**	**-3.662**	**-4.318**	**-2.302**	**-2.211**	**-1.730**	0.311	1.787
	(0.765)	(0.709)	(0.716)	(0.478)	**(0.002)**	**(0.001)**	**(0.000)**	**(0.014)**	**(0.018)**	**(0.047)**	(0.621)	(0.958)
AR+RNN	4.453	1.964	1.969	2.618	-0.924	-1.242	-1.502	**-1.769**	**-1.716**	-1.243	2.865	3.475
	(1.000)	(0.970)	(0.971)	(0.993)	(0.182)	(0.112)	(0.072)	**(0.044)**	**(0.049)**	(0.112)	(0.996)	(0.999)
Ave. BM	-1.005	-1.167	-1.169	**-1.765**	**-5.287**	**-5.131**	**-6.156**	**-3.061**	**-3.117**	**-2.529**	**-2.515**	-1.511
	(0.162)	(0.127)	(0.126)	**(0.044)**	**(0.000)**	**(0.000)**	**(0.000)**	**(0.002)**	**(0.002)**	**(0.009)**	**(0.009)**	(0.071)
Ave. Linear	1.728	1.923	1.986	1.155	**-3.105**	**-3.165**	**-3.813**	**-2.041**	**-1.905**	-1.497	2.154	3.044
	(0.953)	(0.968)	(0.972)	(0.871)	**(0.002)**	**(0.002)**	**(0.000)**	**(0.025)**	**(0.034)**	(0.073)	(0.980)	(0.997)
Ave. Local	0.583	0.239	0.251	-0.895	**-2.808**	**-3.068**	**-3.898**	**-2.361**	**-2.298**	**-1.863**	-0.397	1.089
	(0.718)	(0.594)	(0.598)	(0.189)	**(0.004)**	**(0.002)**	**(0.000)**	**(0.013)**	**(0.015)**	**(0.037)**	(0.347)	(0.857)
Ave. Non-linear	-0.772	-0.843	-0.836	-1.308	**-4.431**	**-4.134**	**-5.027**	**-3.020**	**-3.081**	**-2.553**	-1.640	-0.925
	(0.223)	(0.203)	(0.205)	(0.101)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.003)**	**(0.002)**	**(0.008)**	(0.056)	(0.181)
Ave. AR+	0.938	0.330	0.345	-0.475	**-3.135**	**-3.358**	**-3.821**	**-2.591**	**-2.602**	**-2.076**	-0.322	0.957
	(0.822)	(0.628)	(0.634)	(0.319)	**(0.002)**	**(0.001)**	**(0.000)**	**(0.008)**	**(0.007)**	**(0.024)**	(0.375)	(0.827)
Tot. Ave.	0.143	-0.160	-0.155	-1.084	**-4.538**	**-4.404**	**-5.482**	**-2.796**	**-2.787**	**-2.250**	-1.569	-0.090
	(0.556)	(0.437)	(0.439)	(0.144)	**(0.000)**	**(0.000)**	**(0.000)**	**(0.005)**	**(0.005)**	**(0.016)**	(0.064)	(0.464)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.53: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 3$. $N = 29$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	-0.482	-1.077	**-1.715**	-1.669	-1.037	-1.343	0.432	-0.494	**-2.641**	-1.007	-0.414	0.768
	(0.317)	(0.145)	**(0.049)**	(0.053)	(0.154)	(0.095)	(0.666)	(0.313)	**(0.007)**	(0.161)	(0.341)	(0.776)
RW	-0.220	-1.114	**-1.795**	**-1.736**	-0.842	-0.935	0.405	-0.360	**-2.570**	-1.055	-0.142	1.077
	(0.414)	(0.137)	**(0.042)**	**(0.047)**	(0.203)	(0.179)	(0.656)	(0.361)	**(0.008)**	(0.150)	(0.444)	(0.855)
DDD	-0.232	-1.126	**-1.802**	**-1.742**	-0.877	-0.967	0.403	-0.372	**-2.527**	-1.071	-0.150	1.079
	(0.409)	(0.135)	**(0.041)**	**(0.046)**	(0.194)	(0.171)	(0.655)	(0.356)	**(0.009)**	(0.147)	(0.441)	(0.855)
VAR(4)	0.550	-0.995	**-1.810**	**-1.735**	-0.726	-1.166	1.616	0.359	-1.664	-0.723	0.734	1.373
	(0.707)	(0.164)	**(0.041)**	**(0.047)**	(0.237)	(0.127)	(0.941)	(0.639)	(0.054)	(0.238)	(0.766)	(0.910)
GETS	4.473	0.876	-0.805	-0.853	1.948	1.610	3.750	5.125	0.020	1.404	4.197	4.789
	(1.000)	(0.806)	(0.214)	(0.201)	(0.969)	(0.941)	(1.000)	(1.000)	(0.508)	(0.914)	(1.000)	(1.000)
GETS-IIS	4.263	1.373	-0.739	-0.786	2.216	1.833	3.864	6.059	0.280	2.039	4.601	4.321
	(1.000)	(0.910)	(0.233)	(0.219)	(0.982)	(0.961)	(1.000)	(1.000)	(0.609)	(0.975)	(1.000)	(1.000)
GETS-SIS	5.763	1.289	-0.376	-0.440	2.961	2.569	4.529	4.851	0.851	1.731	4.770	5.721
	(1.000)	(0.896)	(0.355)	(0.332)	(0.997)	(0.992)	(1.000)	(1.000)	(0.799)	(0.953)	(1.000)	(1.000)
GETS-DDD	2.379	1.236	0.078	0.018	1.921	1.701	2.751	2.463	1.067	1.841	2.305	3.040
	(0.988)	(0.887)	(0.531)	(0.507)	(0.968)	(0.950)	(0.995)	(0.990)	(0.853)	(0.962)	(0.986)	(0.997)
GETS-IIS-DDD	2.320	1.090	-0.041	-0.095	1.794	1.586	2.792	2.360	0.937	1.709	2.259	3.064
	(0.986)	(0.857)	(0.484)	(0.463)	(0.958)	(0.938)	(0.995)	(0.987)	(0.822)	(0.951)	(0.984)	(0.998)
GETS-SIS-DDD	1.898	0.851	-0.105	-0.151	1.442	1.300	2.286	1.873	0.670	1.279	1.831	2.538
	(0.966)	(0.799)	(0.459)	(0.440)	(0.920)	(0.898)	(0.985)	(0.964)	(0.746)	(0.894)	(0.961)	(0.992)
Ridge, CV	0.832	-1.035	**-1.772**	**-1.737**	-1.057	-1.488	1.982	0.108	**-1.961**	-0.791	0.491	1.867
	(0.794)	(0.155)	**(0.044)**	**(0.047)**	(0.150)	(0.074)	(0.971)	(0.543)	**(0.030)**	(0.218)	(0.686)	(0.964)
Lasso, CV	-1.628	-1.306	**-1.920**	**-1.869**	**-2.205**	**-2.598**	0.668	-0.775	**-2.461**	-1.167	-0.340	1.382
	(0.057)	(0.101)	**(0.033)**	**(0.036)**	**(0.018)**	**(0.007)**	(0.745)	(0.222)	**(0.010)**	(0.126)	(0.368)	(0.911)
ELNET, CV	-	-1.121	**-1.805**	**-1.778**	-1.442	**-1.769**	1.177	-0.226	**-2.023**	-0.902	0.119	1.721
	-	(0.136)	**(0.041)**	**(0.043)**	(0.080)	**(0.044)**	(0.875)	(0.412)	**(0.026)**	(0.188)	(0.547)	(0.952)
Ridge, AIC	1.121	-	**-2.769**	**-2.451**	0.616	0.418	1.335	1.514	-0.565	0.779	1.256	1.479
	(0.864)	-	**(0.005)**	**(0.010)**	(0.728)	(0.660)	(0.904)	(0.929)	(0.288)	(0.779)	(0.890)	(0.925)
Lasso, AIC	1.805	2.769	-	-0.465	1.489	1.309	1.910	2.156	0.673	2.070	1.959	1.986
	(0.959)	(0.995)	-	(0.323)	(0.926)	(0.899)	(0.967)	(0.980)	(0.747)	(0.976)	(0.970)	(0.972)
ELNET, AIC	1.778	2.451	0.465	-	1.460	1.295	1.853	2.080	0.687	1.864	1.910	1.936
	(0.957)	(0.990)	(0.677)	-	(0.922)	(0.897)	(0.963)	(0.977)	(0.751)	(0.964)	(0.967)	(0.968)
k-NN	1.442	-0.616	-1.489	-1.460	-	-0.693	1.657	0.906	-1.193	-0.308	0.808	1.867
	(0.920)	(0.272)	(0.074)	(0.078)	-	(0.247)	(0.946)	(0.814)	(0.121)	(0.380)	(0.787)	(0.964)
wk-NN	1.769	-0.418	-1.309	-1.295	0.693	-	2.082	0.965	-1.055	-0.108	0.993	2.096
	(0.956)	(0.340)	(0.101)	(0.103)	(0.753)	-	(0.977)	(0.829)	(0.150)	(0.457)	(0.835)	(0.977)
RF	-1.177	-1.335	**-1.910**	**-1.853**	-1.657	**-2.082**	-	-0.907	**-2.747**	-1.286	-0.970	0.751
	(0.125)	(0.096)	**(0.033)**	**(0.037)**	(0.054)	**(0.023)**	-	(0.186)	**(0.005)**	(0.104)	(0.170)	(0.771)
FFNN	0.226	-1.514	**-2.156**	**-2.080**	-0.906	-0.965	0.907	-	**-2.049**	-1.272	0.288	1.348
	(0.588)	(0.071)	**(0.020)**	**(0.023)**	(0.186)	(0.171)	(0.814)	-	**(0.025)**	(0.107)	(0.612)	(0.906)
RNN	2.023	0.565	-0.673	-0.687	1.193	1.055	2.747	2.049	-	0.943	2.929	3.533
	(0.974)	(0.712)	(0.253)	(0.249)	(0.879)	(0.850)	(0.995)	(0.975)	-	(0.823)	(0.997)	(0.999)
SVR-LIN	0.902	-0.779	**-2.070**	**-1.864**	0.308	0.108	1.286	1.272	-0.943	-	1.037	1.458
	(0.812)	(0.221)	**(0.024)**	**(0.036)**	(0.620)	(0.543)	(0.896)	(0.893)	(0.177)	-	(0.846)	(0.922)
SVR-POLY	-0.119	-1.256	**-1.959**	**-1.910**	-0.808	-0.993	0.970	-0.288	**-2.929**	-1.037	-	1.298
	(0.453)	(0.110)	**(0.030)**	**(0.033)**	(0.213)	(0.165)	(0.830)	(0.388)	**(0.003)**	(0.154)	-	(0.898)
SVR-RBF	**-1.721**	-1.479	**-1.986**	**-1.936**	**-1.867**	**-2.096**	-0.751	-1.348	**-3.533**	-1.458	-1.298	-
	(0.048)	(0.075)	**(0.028)**	**(0.032)**	**(0.036)**	**(0.023)**	(0.229)	(0.094)	**(0.001)**	(0.078)	(0.102)	-
SVR-ANOVA	0.880	-0.510	-1.466	-1.403	0.238	-0.020	1.426	0.864	-0.962	-0.190	0.859	1.471
	(0.807)	(0.307)	(0.077)	(0.086)	(0.593)	(0.492)	(0.918)	(0.802)	(0.172)	(0.425)	(0.801)	(0.924)
AR+SVR-POLY	-0.077	-0.984	-1.663	-1.624	-1.072	-1.484	2.189	-0.197	**-2.431**	-0.869	0.054	1.989
	(0.469)	(0.167)	(0.054)	(0.058)	(0.146)	(0.074)	(0.981)	(0.422)	**(0.011)**	(0.196)	(0.521)	(0.972)
AR+SVR-RBF	-0.068	-0.901	-1.587	-1.550	-0.845	-1.195	1.132	-0.174	**-2.375**	-0.780	0.030	1.637
	(0.473)	(0.188)	(0.062)	(0.066)	(0.203)	(0.121)	(0.866)	(0.432)	**(0.012)**	(0.221)	(0.512)	(0.944)
AR+SVR-ANOVA	0.385	-0.999	**-1.725**	-1.663	-1.020	-1.374	2.048	0.129	**-1.855**	-0.859	0.504	1.786
	(0.649)	(0.163)	**(0.048)**	(0.054)	(0.158)	(0.090)	(0.975)	(0.551)	**(0.037)**	(0.199)	(0.691)	(0.958)
AR+FFNN	0.723	-1.019	**-1.779**	**-1.712**	-0.719	**-1.994**	1.340	0.467	**-1.783**	-0.788	0.516	1.817
	(0.762)	(0.158)	**(0.043)**	**(0.049)**	(0.239)	**(0.028)**	(0.905)	(0.678)	**(0.043)**	(0.219)	(0.695)	(0.960)
AR+RNN	2.466	0.048	-1.098	-1.084	1.153	1.076	4.526	2.325	-0.869	0.523	2.263	3.376
	(0.990)	(0.519)	(0.141)	(0.144)	(0.871)	(0.854)	(1.000)	(0.986)	(0.196)	(0.697)	(0.984)	(0.999)
Ave. BM	**-1.981**	-1.644	**-2.117**	**-2.049**	**-2.019**	**-2.223**	-1.308	-1.569	**-3.450**	-1.667	**-2.708**	-0.326
	(0.029)	(0.056)	**(0.022)**	**(0.025)**	**(0.027)**	**(0.017)**	(0.101)	(0.064)	**(0.001)**	(0.053)	**(0.006)**	(0.373)
Ave. Linear	2.743	-0.431	-1.508	-1.511	0.465	0.189	2.719	3.558	-1.502	0.030	1.959	3.254
	(0.995)	(0.335)	(0.071)	(0.071)	(0.677)	(0.574)	(0.994)	(0.999)	(0.072)	(0.512)	(0.970)	(0.999)
Ave. Local	0.108	-1.028	**-1.722**	-1.671	**-1.793**	**-2.900**	1.328	-0.105	**-1.935**	-0.877	0.151	1.415
	(0.542)	(0.156)	**(0.048)**	(0.053)	**(0.042)**	**(0.004)**	(0.903)	(0.458)	**(0.032)**	(0.194)	(0.560)	(0.916)
Ave. Non-linear	-1.344	-1.411	**-1.951**	**-1.903**	-1.539	**-1.761**	-0.616	-1.141	**-3.353**	-1.385	-1.299	0.468
	(0.095)	(0.085)	**(0.031)**	**(0.034)**	(0.067)	**(0.045)**	(0.272)	(0.132)	**(0.001)**	(0.088)	(0.102)	(0.678)
Ave. AR+	0.114	-0.994	-1.696	-1.646	-1.105	-1.594	2.374	-0.102	**-2.283**	-0.867	0.198	2.249
	(0.545)	(0.164)	(0.051)	(0.055)	(0.139)	(0.061)	(0.988)	(0.460)	**(0.015)**	(0.197)	(0.578)	(0.984)
Tot. Ave.	-0.913	-1.302	**-1.914**	**-1.867**	-1.429	-1.675	0.970	-0.784	**-2.940**	-1.211	-0.510	1.829
	(0.185)	(0.102)	**(0.033)**	**(0.036)**	(0.082)	(0.053)	(0.830)	(0.220)	**(0.003)**	(0.118)	(0.307)	(0.961)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.54: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 3$. $N = 29$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.064	-0.780	-0.951	-0.885	-0.733	**-4.453**	1.005	**-1.728**	-0.583	0.772	-0.938	-0.143
	(0.148)	(0.221)	(0.175)	(0.192)	(0.235)	**(0.000)**	(0.838)	**(0.047)**	(0.282)	(0.777)	(0.178)	(0.444)
RW	-0.931	-0.217	-0.182	-0.431	-0.555	**-1.964**	1.167	**-1.923**	-0.239	0.843	-0.330	0.160
	(0.180)	(0.415)	(0.428)	(0.335)	(0.291)	**(0.030)**	(0.873)	**(0.032)**	(0.406)	(0.797)	(0.372)	(0.563)
DDD	-0.960	-0.231	-0.190	-0.447	-0.577	**-1.969**	1.169	**-1.986**	-0.251	0.836	-0.345	0.155
	(0.173)	(0.409)	(0.425)	(0.329)	(0.284)	**(0.029)**	(0.874)	**(0.028)**	(0.402)	(0.795)	(0.366)	(0.561)
VAR(4)	-0.754	0.578	0.431	0.350	0.056	**-2.618**	1.765	-1.155	0.895	1.308	0.475	1.084
	(0.228)	(0.716)	(0.665)	(0.635)	(0.522)	**(0.007)**	(0.956)	(0.129)	(0.811)	(0.899)	(0.681)	(0.856)
GETS	1.241	3.088	2.631	2.920	3.183	0.924	5.287	3.105	2.808	4.431	3.135	4.538
	(0.887)	(0.998)	(0.993)	(0.997)	(0.998)	(0.818)	(1.000)	(0.998)	(0.996)	(1.000)	(0.998)	(1.000)
GETS-IIS	1.577	3.238	2.722	3.467	3.662	1.242	5.131	3.165	3.068	4.134	3.358	4.404
	(0.937)	(0.998)	(0.994)	(0.999)	(0.999)	(0.888)	(1.000)	(0.998)	(0.998)	(1.000)	(0.999)	(1.000)
GETS-SIS	1.842	3.987	3.081	3.716	4.318	1.502	6.156	3.813	3.898	5.027	3.821	5.482
	(0.962)	(1.000)	(0.998)	(1.000)	(1.000)	(0.928)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)	(1.000)
GETS-DDD	2.054	2.546	2.571	2.334	2.302	1.769	3.061	2.041	2.361	3.020	2.591	2.796
	(0.975)	(0.992)	(0.992)	(0.986)	(0.986)	(0.956)	(0.998)	(0.975)	(0.987)	(0.997)	(0.992)	(0.995)
GETS-IIS-DDD	1.946	2.536	2.617	2.309	2.211	1.716	3.117	1.905	2.298	3.081	2.602	2.787
	(0.969)	(0.991)	(0.993)	(0.986)	(0.982)	(0.951)	(0.998)	(0.966)	(0.985)	(0.998)	(0.993)	(0.995)
GETS-SIS-DDD	1.464	2.091	2.184	1.827	1.730	1.243	2.529	1.497	1.863	2.553	2.076	2.250
	(0.923)	(0.977)	(0.981)	(0.961)	(0.953)	(0.888)	(0.991)	(0.927)	(0.963)	(0.992)	(0.976)	(0.984)
Ridge, CV	-0.767	0.481	0.326	-0.053	-0.311	**-2.865**	2.515	**-2.154**	0.397	1.640	0.322	1.569
	(0.225)	(0.683)	(0.627)	(0.479)	(0.379)	**(0.004)**	(0.991)	**(0.020)**	(0.653)	(0.944)	(0.625)	(0.936)
Lasso, CV	-1.179	-0.545	-0.376	-1.033	**-1.787**	**-3.475**	1.511	**-3.044**	-1.089	0.925	-0.957	0.090
	(0.124)	(0.295)	(0.355)	(0.155)	**(0.042)**	**(0.001)**	(0.929)	**(0.003)**	(0.143)	(0.819)	(0.173)	(0.536)
ELNET, CV	-0.880	0.077	0.068	-0.385	-0.723	**-2.466**	1.981	**-2.743**	-0.108	1.344	-0.114	0.913
	(0.193)	(0.531)	(0.527)	(0.351)	(0.238)	**(0.010)**	(0.971)	**(0.005)**	(0.458)	(0.905)	(0.455)	(0.815)
Ridge, AIC	0.510	0.984	0.901	0.999	1.019	-0.048	1.644	0.431	1.028	1.411	0.994	1.302
	(0.693)	(0.833)	(0.812)	(0.837)	(0.842)	(0.481)	(0.944)	(0.665)	(0.844)	(0.915)	(0.836)	(0.898)
Lasso, AIC	1.466	1.663	1.587	1.725	1.779	1.098	2.117	1.508	1.722	1.951	1.696	1.914
	(0.923)	(0.946)	(0.938)	(0.952)	(0.957)	(0.859)	(0.978)	(0.929)	(0.952)	(0.969)	(0.949)	(0.967)
ELNET, AIC	1.403	1.624	1.550	1.663	1.712	1.084	2.049	1.511	1.671	1.903	1.646	1.867
	(0.914)	(0.942)	(0.934)	(0.946)	(0.951)	(0.856)	(0.975)	(0.929)	(0.947)	(0.966)	(0.945)	(0.964)
k-NN	-0.238	1.072	0.845	1.020	0.719	-1.153	2.019	-0.465	1.793	1.539	1.105	1.429
	(0.407)	(0.854)	(0.797)	(0.842)	(0.761)	(0.129)	(0.973)	(0.323)	(0.958)	(0.933)	(0.861)	(0.918)
wk-NN	0.020	1.484	1.195	1.374	1.994	-1.076	2.223	-0.189	2.900	1.761	1.594	1.675
	(0.508)	(0.926)	(0.879)	(0.910)	(0.972)	(0.146)	(0.983)	(0.426)	(0.996)	(0.955)	(0.939)	(0.947)
RF	-1.426	**-2.189**	-1.132	**-2.048**	-1.340	**-4.526**	1.308	**-2.719**	-1.328	0.616	**-2.374**	-0.970
	(0.082)	**(0.019)**	(0.134)	**(0.025)**	(0.095)	**(0.000)**	(0.899)	**(0.006)**	(0.097)	(0.728)	**(0.012)**	(0.170)
FFNN	-0.864	0.197	0.174	-0.129	-0.467	**-2.325**	1.569	**-3.558**	0.105	1.141	0.102	0.784
	(0.198)	(0.578)	(0.568)	(0.449)	(0.322)	**(0.014)**	(0.936)	**(0.001)**	(0.542)	(0.868)	(0.540)	(0.780)
RNN	0.962	2.431	2.375	1.855	1.783	0.869	3.450	1.502	1.935	3.353	2.283	2.940
	(0.828)	(0.989)	(0.988)	(0.963)	(0.957)	(0.804)	(0.999)	(0.928)	(0.968)	(0.999)	(0.985)	(0.997)
SVR-LIN	0.190	0.869	0.780	0.859	0.788	-0.523	1.667	-0.030	0.877	1.385	0.867	1.211
	(0.575)	(0.804)	(0.779)	(0.801)	(0.781)	(0.303)	(0.947)	(0.488)	(0.806)	(0.912)	(0.803)	(0.882)
SVR-POLY	-0.859	-0.054	-0.030	-0.504	-0.516	**-2.263**	2.708	**-1.959**	-0.151	1.299	-0.198	0.510
	(0.199)	(0.479)	(0.488)	(0.309)	(0.305)	**(0.016)**	(0.994)	**(0.030)**	(0.440)	(0.898)	(0.422)	(0.693)
SVR-RBF	-1.471	**-1.989**	-1.637	**-1.786**	**-1.817**	**-3.376**	0.326	**-3.254**	-1.415	-0.468	**-2.249**	**-1.829**
	(0.076)	**(0.028)**	(0.056)	**(0.042)**	**(0.040)**	**(0.001)**	(0.627)	**(0.001)**	(0.084)	(0.322)	**(0.016)**	**(0.039)**
SVR-ANOVA	-	0.963	0.781	0.989	0.720	-0.700	1.764	-0.184	1.049	1.388	0.900	1.200
	-	(0.828)	(0.779)	(0.835)	(0.761)	(0.245)	(0.956)	(0.428)	(0.848)	(0.912)	(0.812)	(0.880)
AR+SVR-POLY	-0.963	-	0.027	-0.619	-0.557	**-3.994**	2.874	**-1.797**	-0.195	1.886	-1.001	0.864
	(0.172)	-	(0.511)	(0.270)	(0.291)	**(0.000)**	(0.996)	**(0.042)**	(0.424)	(0.965)	(0.163)	(0.803)
AR+SVR-RBF	-0.781	-0.027	-	-0.369	-0.437	**-4.464**	1.572	-1.442	-0.144	1.547	-0.300	0.499
	(0.221)	(0.489)	-	(0.357)	(0.333)	**(0.000)**	(0.936)	(0.080)	(0.443)	(0.933)	(0.383)	(0.689)
AR+SVR-ANOVA	-0.989	0.619	0.369	-	-0.235	**-2.719**	2.468	-1.580	0.494	1.692	0.423	1.325
	(0.165)	(0.730)	(0.643)	-	(0.408)	**(0.006)**	(0.990)	(0.063)	(0.688)	(0.949)	(0.662)	(0.902)
AR+FFNN	-0.720	0.557	0.437	0.235	-	**-2.067**	1.890	-1.500	1.041	1.407	0.503	1.202
	(0.239)	(0.709)	(0.667)	(0.592)	-	**(0.024)**	(0.965)	(0.072)	(0.847)	(0.915)	(0.691)	(0.880)
AR+RNN	0.700	3.994	4.464	2.719	2.067	-	3.618	0.868	3.393	3.529	3.989	3.653
	(0.755)	(1.000)	(1.000)	(0.994)	(0.976)	-	(0.999)	(0.804)	(0.999)	(0.999)	(1.000)	(0.999)
Ave. BM	**-1.764**	**-2.874**	-1.572	**-2.468**	**-1.890**	**-3.618**	-	**-4.138**	-1.673	-0.878	**-2.532**	**-3.481**
	(0.044)	**(0.004)**	(0.064)	**(0.010)**	**(0.035)**	**(0.001)**	-	**(0.000)**	(0.053)	(0.194)	**(0.009)**	**(0.001)**
Ave. Linear	0.184	1.797	1.442	1.580	1.500	-0.868	4.138	-	1.506	3.120	1.912	3.562
	(0.572)	(0.958)	(0.920)	(0.937)	(0.928)	(0.196)	(1.000)	-	(0.928)	(0.998)	(0.967)	(0.999)
Ave. Local	-1.049	0.195	0.144	-0.494	-1.041	**-3.393**	1.673	-1.506	-	1.130	-0.020	0.717
	(0.152)	(0.576)	(0.557)	(0.312)	(0.153)	**(0.001)**	(0.947)	(0.072)	-	(0.866)	(0.492)	(0.760)
Ave. Non-linear	-1.388	**-1.886**	-1.547	-1.692	-1.407	**-3.529**	0.878	**-3.120**	-1.130	-	**-2.029**	-1.607
	(0.088)	**(0.035)**	(0.067)	(0.051)	(0.085)	**(0.001)**	(0.806)	**(0.002)**	(0.134)	-	**(0.026)**	(0.060)
Ave. AR+	-0.900	1.001	0.300	-0.423	-0.503	**-3.989**	2.532	**-1.912**	0.020	2.029	-	1.359
	(0.188)	(0.837)	(0.617)	(0.338)	(0.309)	**(0.000)**	(0.991)	**(0.033)**	(0.508)	(0.974)	-	(0.908)
Tot. Ave.	-1.200	-0.864	-0.499	-1.325	-1.202	**-3.653**	3.481	**-3.562**	-0.717	1.607	-1.359	-
	(0.120)	(0.197)	(0.311)	(0.098)	(0.120)	**(0.001)**	(0.999)	**(0.001)**	(0.240)	(0.940)	(0.092)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.55: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 4$. $N = 28$.

	AR(1)	RW	DDD	VAR(4)	GETS	GETS-IIS	GETS-SIS	GETS-DDD	GETS-IIS-DDD	GETS-SIS-DDD	Ridge, CV	Lasso, CV
AR(1)	-	-1.003	-0.835	-1.647	-1.356	-1.500	**-2.170**	-1.489	-1.619	**-1.744**	0.306	0.524
	-	(0.162)	(0.205)	(0.056)	(0.093)	(0.073)	**(0.019)**	(0.074)	(0.059)	**(0.046)**	(0.619)	(0.698)
RW	1.003	-	1.343	0.275	-1.164	-1.204	**-1.794**	-1.493	-1.654	**-1.888**	1.281	1.590
	(0.838)	-	(0.905)	(0.607)	(0.127)	(0.120)	**(0.042)**	(0.074)	(0.055)	**(0.035)**	(0.894)	(0.938)
DDD	0.835	-1.343	-	0.054	-1.211	-1.266	**-1.804**	-1.525	-1.697	**-1.924**	1.148	1.494
	(0.795)	(0.095)	-	(0.521)	(0.118)	(0.108)	**(0.041)**	(0.069)	(0.051)	**(0.032)**	(0.869)	(0.927)
VAR(4)	1.647	-0.275	-0.054	-	-1.254	-1.434	**-2.205**	-1.354	-1.460	-1.542	1.811	1.628
	(0.944)	(0.393)	(0.479)	-	(0.110)	(0.081)	**(0.018)**	(0.093)	(0.078)	(0.067)	(0.959)	(0.942)
GETS	1.356	1.164	1.211	1.254	-	0.285	-0.424	-0.709	-0.207	0.274	1.469	1.472
	(0.907)	(0.873)	(0.882)	(0.890)	-	(0.611)	(0.338)	(0.242)	(0.419)	(0.607)	(0.923)	(0.924)
GETS-IIS	1.500	1.204	1.266	1.434	-0.285	-	-0.692	-0.581	-0.314	0.108	1.673	1.641
	(0.927)	(0.880)	(0.892)	(0.919)	(0.389)	-	(0.248)	(0.283)	(0.378)	(0.543)	(0.947)	(0.944)
GETS-SIS	2.170	1.794	1.804	2.205	0.424	0.692	-	-0.063	0.143	1.786	2.389	2.335
	(0.981)	(0.958)	(0.959)	(0.982)	(0.662)	(0.752)	-	(0.475)	(0.556)	(0.957)	(0.988)	(0.986)
GETS-DDD	1.489	1.493	1.525	1.354	0.709	0.581	0.063	-	0.908	1.022	1.545	1.584
	(0.926)	(0.926)	(0.931)	(0.907)	(0.758)	(0.717)	(0.525)	-	(0.814)	(0.842)	(0.933)	(0.938)
GETS-IIS-DDD	1.619	1.654	1.697	1.460	0.207	0.314	-0.143	-0.908	-	1.166	1.689	1.737
	(0.941)	(0.945)	(0.949)	(0.922)	(0.581)	(0.622)	(0.444)	(0.186)	-	(0.873)	(0.949)	(0.953)
GETS-SIS-DDD	1.744	1.888	1.924	1.542	-0.274	-0.108	**-1.786**	-1.022	-1.166	-	1.843	1.902
	(0.954)	(0.965)	(0.968)	(0.933)	(0.393)	(0.457)	**(0.043)**	(0.158)	(0.127)	-	(0.962)	(0.966)
Ridge, CV	-0.306	-1.281	-1.148	**-1.811**	-1.469	-1.673	**-2.389**	-1.545	-1.689	**-1.843**	-	0.550
	(0.381)	(0.106)	(0.131)	**(0.041)**	(0.077)	(0.053)	**(0.012)**	(0.067)	(0.051)	**(0.038)**	-	(0.707)
Lasso, CV	-0.524	-1.590	-1.494	-1.628	-1.472	-1.641	**-2.335**	-1.584	**-1.737**	**-1.902**	-0.550	-
	(0.302)	(0.062)	(0.073)	(0.058)	(0.076)	(0.056)	**(0.014)**	(0.062)	**(0.047)**	**(0.034)**	(0.293)	-
ELNET, CV	-0.552	-1.628	-1.538	-1.661	-1.479	-1.649	**-2.347**	-1.591	**-1.747**	**-1.914**	-0.612	-1.468
	(0.293)	(0.058)	(0.068)	(0.054)	(0.075)	(0.055)	**(0.013)**	(0.062)	**(0.046)**	**(0.033)**	(0.273)	(0.077)
Ridge, AIC	0.841	0.312	0.453	0.556	-1.156	-1.622	**-3.475**	-1.100	-1.122	-1.114	1.182	1.128
	(0.796)	(0.621)	(0.673)	(0.709)	(0.129)	(0.058)	**(0.001)**	(0.141)	(0.136)	(0.137)	(0.876)	(0.865)
Lasso, AIC	1.243	1.088	1.130	1.194	0.388	1.749	-0.009	-0.060	0.118	0.348	1.362	1.340
	(0.888)	(0.857)	(0.866)	(0.879)	(0.649)	(0.954)	(0.497)	(0.476)	(0.546)	(0.635)	(0.908)	(0.904)
ELNET, AIC	1.328	1.147	1.194	1.283	0.260	0.422	-0.123	-0.154	0.031	0.289	1.467	1.433
	(0.902)	(0.869)	(0.879)	(0.895)	(0.601)	(0.662)	(0.452)	(0.439)	(0.512)	(0.613)	(0.923)	(0.918)
k-NN	-0.515	**-1.857**	**-1.762**	**-1.787**	-1.562	**-1.764**	**-2.474**	-1.651	**-1.830**	**-2.029**	-0.676	-0.133
	(0.305)	**(0.037)**	**(0.045)**	**(0.043)**	(0.065)	**(0.045)**	**(0.010)**	(0.055)	**(0.039)**	**(0.026)**	(0.252)	(0.447)
wk-NN	-0.545	**-2.033**	**-1.994**	**-1.718**	-1.556	**-1.747**	**-2.458**	-1.654	**-1.832**	**-2.035**	-0.703	-0.220
	(0.295)	**(0.026)**	**(0.028)**	**(0.049)**	(0.066)	**(0.046)**	**(0.010)**	(0.055)	**(0.039)**	**(0.026)**	(0.244)	(0.414)
RF	-1.346	**-2.077**	**-2.046**	**-2.743**	-1.586	**-1.782**	**-2.505**	-1.690	**-1.873**	**-2.089**	**-1.820**	-1.034
	(0.095)	**(0.024)**	**(0.025)**	**(0.005)**	(0.062)	**(0.043)**	**(0.009)**	(0.051)	**(0.036)**	**(0.023)**	**(0.040)**	(0.155)
FFNN	0.175	-1.097	-0.922	-0.826	-1.359	-1.549	**-2.258**	-1.452	-1.576	**-1.724**	1.127	1.181
	(0.569)	(0.141)	(0.182)	(0.208)	(0.093)	(0.067)	**(0.016)**	(0.079)	(0.063)	**(0.048)**	(0.865)	(0.876)
RNN	2.396	1.319	1.537	2.037	-0.407	-0.419	-0.825	-0.581	-0.515	-0.374	2.542	2.439
	(0.988)	(0.901)	(0.932)	(0.974)	(0.344)	(0.339)	(0.208)	(0.283)	(0.306)	(0.356)	(0.991)	(0.989)
SVR-LIN	0.420	-0.514	-0.291	-0.281	-1.554	**-1.926**	**-3.387**	-1.517	-1.667	**-1.817**	0.889	0.914
	(0.661)	(0.306)	(0.387)	(0.390)	(0.066)	**(0.032)**	**(0.001)**	(0.070)	(0.054)	**(0.040)**	(0.809)	(0.816)
SVR-POLY	0.478	-0.510	-0.315	-0.313	-1.231	-1.376	**-1.988**	-1.295	-1.367	-1.431	1.362	1.433
	(0.682)	(0.307)	(0.378)	(0.378)	(0.114)	(0.090)	**(0.029)**	(0.103)	(0.091)	(0.082)	(0.908)	(0.918)
SVR-RBF	-0.479	-1.321	-1.204	-1.234	-1.426	-1.561	**-2.112**	-1.540	-1.668	**-1.792**	-0.455	-0.133
	(0.318)	(0.099)	(0.119)	(0.114)	(0.083)	(0.065)	**(0.022)**	(0.068)	(0.053)	**(0.042)**	(0.326)	(0.447)
SVR-ANOVA	1.091	0.968	1.009	0.982	-0.320	0.046	-0.271	-0.557	-0.236	0.112	1.184	1.206
	(0.857)	(0.829)	(0.839)	(0.832)	(0.376)	(0.518)	(0.394)	(0.291)	(0.408)	(0.544)	(0.877)	(0.881)
AR+SVR-POLY	0.552	-0.798	-0.625	-0.835	-1.251	-1.366	**-1.934**	-1.392	-1.496	-1.583	0.891	1.540
	(0.707)	(0.216)	(0.269)	(0.206)	(0.111)	(0.092)	**(0.032)**	(0.088)	(0.073)	(0.063)	(0.810)	(0.932)
AR+SVR-RBF	-0.437	-1.204	-1.087	-1.456	-1.351	-1.490	**-2.077**	-1.488	-1.614	**-1.737**	0.016	0.477
	(0.333)	(0.120)	(0.143)	(0.078)	(0.094)	(0.074)	**(0.024)**	(0.074)	(0.059)	**(0.047)**	(0.506)	(0.682)
AR+SVR-ANOVA	1.830	0.355	0.591	0.722	-1.035	-1.055	-1.559	-1.260	-1.330	-1.315	2.125	2.509
	(0.961)	(0.637)	(0.720)	(0.762)	(0.155)	(0.150)	(0.065)	(0.109)	(0.097)	(0.100)	(0.979)	(0.991)
AR+FFNN	0.589	-0.758	-0.442	-0.310	-1.390	-1.602	**-2.692**	-1.450	-1.583	**-1.742**	1.991	2.040
	(0.720)	(0.228)	(0.331)	(0.379)	(0.088)	(0.060)	**(0.006)**	(0.079)	(0.063)	**(0.046)**	(0.972)	(0.974)
AR+RNN	2.545	0.457	0.611	1.133	-0.758	-0.788	-1.235	-0.910	-0.902	-0.828	1.783	1.920
	(0.992)	(0.674)	(0.727)	(0.867)	(0.227)	(0.219)	(0.114)	(0.186)	(0.188)	(0.207)	(0.957)	(0.967)
Ave. BM	-0.757	-1.700	-1.610	**-2.080**	-1.464	-1.624	**-2.225**	-1.613	**-1.777**	**-1.969**	-0.429	0.039
	(0.228)	(0.050)	(0.059)	**(0.024)**	(0.077)	(0.058)	**(0.017)**	(0.059)	**(0.043)**	**(0.030)**	(0.336)	(0.516)
Ave. Linear	0.960	0.274	0.466	0.560	-1.569	**-1.896**	**-7.215**	-1.617	**-1.812**	**-2.045**	1.301	1.336
	(0.827)	(0.607)	(0.678)	(0.710)	(0.064)	**(0.034)**	**(0.000)**	(0.059)	**(0.041)**	**(0.025)**	(0.898)	(0.904)
Ave. Local	-0.973	**-2.235**	**-2.218**	**-2.457**	-1.615	**-1.825**	**-2.572**	**-1.706**	**-1.898**	**-2.123**	**-1.867**	-0.871
	(0.170)	**(0.017)**	**(0.018)**	**(0.010)**	(0.059)	**(0.040)**	**(0.008)**	**(0.050)**	**(0.034)**	**(0.022)**	**(0.036)**	(0.196)
Ave. Non-linear	-0.378	-1.459	-1.338	-1.397	-1.477	-1.636	**-2.343**	-1.583	**-1.731**	**-1.891**	-0.244	0.413
	(0.354)	(0.078)	(0.096)	(0.087)	(0.076)	(0.057)	**(0.013)**	(0.063)	**(0.047)**	**(0.035)**	(0.404)	(0.658)
Ave. AR+	0.193	-0.817	-0.667	-0.926	-1.256	-1.374	**-1.936**	-1.383	-1.480	-1.561	0.575	1.138
	(0.576)	(0.211)	(0.255)	(0.181)	(0.110)	(0.090)	**(0.032)**	(0.089)	(0.075)	(0.065)	(0.715)	(0.867)
Tot. Ave.	-0.268	-1.407	-1.264	**-1.914**	-1.524	**-1.732**	**-2.564**	-1.613	**-1.777**	**-1.969**	0.109	0.765
	(0.396)	(0.085)	(0.109)	**(0.033)**	(0.070)	**(0.047)**	**(0.008)**	(0.059)	**(0.043)**	**(0.030)**	(0.543)	(0.775)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.56: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 4$. $N = 28$.

	ELNET, CV	Ridge, AIC	Lasso, AIC	ELNET, AIC	k-NN	wk-NN	RF	FFNN	RNN	SVR-LIN	SVR-POLY	SVR-RBF
AR(1)	0.552	-0.841	-1.243	-1.328	0.515	0.545	1.346	-0.175	**-2.396**	-0.420	-0.478	0.479
	(0.707)	(0.204)	(0.112)	(0.098)	(0.695)	(0.705)	(0.905)	(0.431)	**(0.012)**	(0.339)	(0.318)	(0.682)
RW	1.628	-0.312	-1.088	-1.147	1.857	2.033	2.077	1.097	-1.319	0.514	0.510	1.321
	(0.942)	(0.379)	(0.143)	(0.131)	(0.963)	(0.974)	(0.976)	(0.859)	(0.099)	(0.694)	(0.693)	(0.901)
DDD	1.538	-0.453	-1.130	-1.194	1.762	1.994	2.046	0.922	-1.537	0.291	0.315	1.204
	(0.932)	(0.327)	(0.134)	(0.121)	(0.955)	(0.972)	(0.975)	(0.818)	(0.068)	(0.613)	(0.622)	(0.881)
VAR(4)	1.661	-0.556	-1.194	-1.283	1.787	1.718	2.743	0.826	**-2.037**	0.281	0.313	1.234
	(0.946)	(0.291)	(0.121)	(0.105)	(0.957)	(0.951)	(0.995)	(0.792)	**(0.026)**	(0.610)	(0.622)	(0.886)
GETS	1.479	1.156	-0.388	-0.260	1.562	1.556	1.586	1.359	0.407	1.554	1.231	1.426
	(0.925)	(0.871)	(0.351)	(0.399)	(0.935)	(0.934)	(0.938)	(0.907)	(0.656)	(0.934)	(0.886)	(0.917)
GETS-IIS	1.649	1.622	**-1.749**	-0.422	1.764	1.747	1.782	1.549	0.419	1.926	1.376	1.561
	(0.945)	(0.942)	**(0.046)**	(0.338)	(0.955)	(0.954)	(0.957)	(0.933)	(0.661)	(0.968)	(0.910)	(0.935)
GETS-SIS	2.347	3.475	0.009	0.123	2.474	2.458	2.505	2.258	0.825	3.387	1.988	2.112
	(0.987)	(0.999)	(0.503)	(0.548)	(0.990)	(0.990)	(0.991)	(0.984)	(0.792)	(0.999)	(0.971)	(0.978)
GETS-DDD	1.591	1.100	0.060	0.154	1.651	1.654	1.690	1.452	0.581	1.517	1.295	1.540
	(0.938)	(0.859)	(0.524)	(0.561)	(0.945)	(0.945)	(0.949)	(0.921)	(0.717)	(0.930)	(0.897)	(0.932)
GETS-IIS-DDD	1.747	1.122	-0.118	-0.031	1.830	1.832	1.873	1.576	0.515	1.667	1.367	1.668
	(0.954)	(0.864)	(0.454)	(0.488)	(0.961)	(0.961)	(0.964)	(0.937)	(0.694)	(0.946)	(0.909)	(0.947)
GETS-SIS-DDD	1.914	1.114	-0.348	-0.289	2.029	2.035	2.089	1.724	0.374	1.817	1.431	1.792
	(0.967)	(0.863)	(0.365)	(0.387)	(0.974)	(0.974)	(0.977)	(0.952)	(0.644)	(0.960)	(0.918)	(0.958)
Ridge, CV	0.612	-1.182	-1.362	-1.467	0.676	0.703	1.820	-1.127	**-2.542**	-0.889	-1.362	0.455
	(0.727)	(0.124)	(0.092)	(0.077)	(0.748)	(0.756)	(0.960)	(0.135)	**(0.009)**	(0.191)	(0.092)	(0.674)
Lasso, CV	1.468	-1.128	-1.340	-1.433	0.133	0.220	1.034	-1.181	**-2.439**	-0.914	-1.433	0.133
	(0.923)	(0.135)	(0.096)	(0.082)	(0.553)	(0.586)	(0.845)	(0.124)	**(0.011)**	(0.184)	(0.082)	(0.553)
ELNET, CV	-	-1.139	-1.344	-1.439	0.090	0.175	0.989	-1.227	**-2.451**	-0.936	-1.449	0.087
	-	(0.132)	(0.095)	(0.081)	(0.536)	(0.569)	(0.834)	(0.115)	**(0.011)**	(0.179)	(0.079)	(0.534)
Ridge, AIC	1.139	-	-1.346	-1.486	1.326	1.293	1.346	1.012	-1.186	1.145	0.748	1.091
	(0.868)	-	(0.095)	(0.074)	(0.902)	(0.896)	(0.905)	(0.840)	(0.123)	(0.869)	(0.769)	(0.857)
Lasso, AIC	1.344	1.346	-	0.591	1.429	1.413	1.433	1.280	0.559	1.445	1.185	1.310
	(0.905)	(0.905)	-	(0.720)	(0.918)	(0.915)	(0.918)	(0.894)	(0.709)	(0.920)	(0.877)	(0.899)
ELNET, AIC	1.439	1.486	-0.591	-	1.542	1.521	1.544	1.371	0.548	1.583	1.262	1.400
	(0.919)	(0.926)	(0.280)	-	(0.933)	(0.930)	(0.933)	(0.909)	(0.706)	(0.938)	(0.891)	(0.913)
k-NN	-0.090	-1.326	-1.429	-1.542	-	0.414	0.878	-1.440	**-2.499**	-1.244	**-1.711**	0.000
	(0.464)	(0.098)	(0.082)	(0.067)	-	(0.659)	(0.806)	(0.081)	**(0.009)**	(0.112)	**(0.049)**	(0.500)
wk-NN	-0.175	-1.293	-1.413	-1.521	-0.414	-	0.777	-1.489	**-2.471**	-1.200	**-1.718**	-0.059
	(0.431)	(0.104)	(0.085)	(0.070)	(0.341)	-	(0.778)	(0.074)	**(0.010)**	(0.120)	**(0.049)**	(0.477)
RF	-0.989	-1.346	-1.433	-1.544	-0.878	-0.777	-	**-1.875**	**-2.787**	-1.249	**-1.790**	-0.530
	(0.166)	(0.095)	(0.082)	(0.067)	(0.194)	(0.222)	-	**(0.036)**	**(0.005)**	(0.111)	**(0.042)**	(0.300)
FFNN	1.227	-1.012	-1.280	-1.371	1.440	1.489	1.875	-	**-2.499**	-0.465	-0.818	1.179
	(0.885)	(0.160)	(0.106)	(0.091)	(0.919)	(0.926)	(0.964)	-	**(0.009)**	(0.323)	(0.210)	(0.876)
RNN	2.451	1.186	-0.559	-0.548	2.499	2.471	2.787	2.499	-	1.774	1.706	2.150
	(0.989)	(0.877)	(0.291)	(0.294)	(0.991)	(0.990)	(0.995)	(0.991)	-	(0.956)	(0.950)	(0.980)
SVR-LIN	0.936	-1.145	-1.445	-1.583	1.244	1.200	1.249	0.465	**-1.774**	-	0.057	0.820
	(0.821)	(0.131)	(0.080)	(0.062)	(0.888)	(0.880)	(0.889)	(0.677)	**(0.044)**	-	(0.523)	(0.790)
SVR-POLY	1.449	-0.748	-1.185	-1.262	1.711	1.718	1.790	0.818	**-1.706**	-0.057	-	2.249
	(0.921)	(0.231)	(0.123)	(0.109)	(0.951)	(0.951)	(0.958)	(0.790)	**(0.050)**	(0.477)	-	(0.984)
SVR-RBF	-0.087	-1.091	-1.310	-1.400	0.000	0.059	0.530	-1.179	**-2.150**	-0.820	**-2.249**	-
	(0.466)	(0.143)	(0.101)	(0.087)	(0.500)	(0.523)	(0.700)	(0.124)	**(0.020)**	(0.210)	**(0.016)**	-
SVR-ANOVA	1.212	0.822	-0.317	-0.215	1.279	1.278	1.290	1.082	0.287	1.201	0.993	1.184
	(0.882)	(0.791)	(0.377)	(0.416)	(0.894)	(0.894)	(0.896)	(0.856)	(0.612)	(0.880)	(0.835)	(0.877)
AR+SVR-POLY	1.564	-0.725	-1.168	-1.239	0.914	0.995	2.185	0.109	**-2.101**	-0.257	-0.336	1.091
	(0.935)	(0.237)	(0.127)	(0.113)	(0.816)	(0.836)	(0.981)	(0.543)	**(0.023)**	(0.400)	(0.370)	(0.858)
AR+SVR-RBF	0.525	-0.944	-1.253	-1.335	0.342	0.403	1.347	-0.555	**-2.502**	-0.595	-0.903	0.410
	(0.698)	(0.177)	(0.110)	(0.097)	(0.632)	(0.655)	(0.905)	(0.292)	**(0.009)**	(0.278)	(0.187)	(0.658)
AR+SVR-ANOVA	2.526	-0.077	-0.944	-0.987	2.281	2.416	2.963	1.409	-0.901	0.851	1.035	2.442
	(0.991)	(0.469)	(0.177)	(0.166)	(0.985)	(0.989)	(0.997)	(0.915)	(0.188)	(0.799)	(0.845)	(0.989)
AR+FFNN	2.094	-0.775	-1.260	-1.351	2.973	2.951	2.346	0.939	**-1.828**	0.048	0.146	1.539
	(0.977)	(0.223)	(0.109)	(0.094)	(0.997)	(0.997)	(0.987)	(0.822)	**(0.039)**	(0.519)	(0.557)	(0.932)
AR+RNN	1.924	0.119	-0.788	-0.810	1.717	1.715	2.288	1.228	-0.763	0.813	1.005	1.746
	(0.968)	(0.547)	(0.219)	(0.213)	(0.951)	(0.951)	(0.985)	(0.885)	(0.226)	(0.788)	(0.838)	(0.954)
Ave. BM	0.095	-1.163	-1.362	-1.464	0.212	0.324	1.349	-1.178	**-2.728**	-0.885	-1.139	0.117
	(0.538)	(0.127)	(0.092)	(0.077)	(0.583)	(0.626)	(0.906)	(0.125)	**(0.006)**	(0.192)	(0.132)	(0.546)
Ave. Linear	1.355	-0.159	-1.299	-1.423	1.587	1.568	1.630	0.994	-0.979	1.348	0.650	1.200
	(0.907)	(0.437)	(0.102)	(0.083)	(0.938)	(0.936)	(0.943)	(0.835)	(0.168)	(0.906)	(0.739)	(0.880)
Ave. Local	-0.831	-1.421	-1.461	-1.578	-1.574	-1.275	0.198	**-2.118**	**-2.753**	-1.427	**-1.983**	-0.458
	(0.207)	(0.083)	(0.078)	(0.063)	(0.064)	(0.107)	(0.578)	**(0.022)**	**(0.005)**	(0.083)	**(0.029)**	(0.325)
Ave. Non-linear	0.506	-1.067	-1.324	-1.417	0.413	0.563	1.266	-0.979	**-2.144**	-0.833	-1.422	0.537
	(0.691)	(0.148)	(0.098)	(0.084)	(0.659)	(0.711)	(0.892)	(0.168)	**(0.021)**	(0.206)	(0.083)	(0.702)
Ave. AR+	1.160	-0.769	-1.177	-1.248	0.704	0.770	1.591	-0.076	**-2.067**	-0.347	-0.513	0.931
	(0.872)	(0.224)	(0.125)	(0.111)	(0.756)	(0.776)	(0.938)	(0.470)	**(0.024)**	(0.366)	(0.306)	(0.820)
Tot. Ave.	0.869	-1.152	-1.381	-1.488	1.385	1.370	2.087	-0.813	**-2.347**	-0.995	-1.080	0.433
	(0.804)	(0.130)	(0.089)	(0.074)	(0.911)	(0.909)	(0.977)	(0.212)	**(0.013)**	(0.164)	(0.145)	(0.666)

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

Table A.3.57: Modified Diebold-Marino (DM) test for equal forecast accuracy. Inflation. Multivariate. $h = 4$. $N = 28$.

	SVR-ANOVA	AR+SVR-POLY	AR+SVR-RBF	AR+SVR-ANOVA	AR+FFNN	AR+RNN	Ave. BM	Ave. Linear	Ave. Local	Ave. Non-linear	Ave. AR+	Tot. Ave.
AR(1)	-1.091	-0.552	0.437	**-1.830**	-0.589	**-2.545**	0.757	-0.960	0.973	0.378	-0.193	0.268
	(0.143)	(0.293)	(0.667)	**(0.039)**	(0.280)	**(0.008)**	(0.772)	(0.173)	(0.830)	(0.646)	(0.424)	(0.604)
RW	-0.968	0.798	1.204	-0.355	0.758	-0.457	1.700	-0.274	2.235	1.459	0.817	1.407
	(0.171)	(0.784)	(0.880)	(0.363)	(0.772)	(0.326)	(0.950)	(0.393)	(0.983)	(0.922)	(0.789)	(0.915)
DDD	-1.009	0.625	1.087	-0.591	0.442	-0.611	1.610	-0.466	2.218	1.338	0.667	1.264
	(0.161)	(0.731)	(0.857)	(0.280)	(0.669)	(0.273)	(0.941)	(0.322)	(0.982)	(0.904)	(0.745)	(0.891)
VAR(4)	-0.982	0.835	1.456	-0.722	0.310	-1.133	2.080	-0.560	2.457	1.397	0.926	1.914
	(0.168)	(0.794)	(0.922)	(0.238)	(0.621)	(0.133)	(0.976)	(0.290)	(0.990)	(0.913)	(0.819)	(0.967)
GETS	0.320	1.251	1.351	1.035	1.390	0.758	1.464	1.569	1.615	1.477	1.256	1.524
	(0.624)	(0.889)	(0.906)	(0.845)	(0.912)	(0.773)	(0.923)	(0.936)	(0.941)	(0.924)	(0.890)	(0.930)
GETS-IIS	-0.046	1.366	1.490	1.055	1.602	0.788	1.624	1.896	1.825	1.636	1.374	1.732
	(0.482)	(0.908)	(0.926)	(0.850)	(0.940)	(0.781)	(0.942)	(0.966)	(0.960)	(0.943)	(0.910)	(0.953)
GETS-SIS	0.271	1.934	2.077	1.559	2.692	1.235	2.225	7.215	2.572	2.343	1.936	2.564
	(0.606)	(0.968)	(0.976)	(0.935)	(0.994)	(0.886)	(0.983)	(1.000)	(0.992)	(0.987)	(0.968)	(0.992)
GETS-DDD	0.557	1.392	1.488	1.260	1.450	0.910	1.613	1.617	1.706	1.583	1.383	1.613
	(0.709)	(0.912)	(0.926)	(0.891)	(0.921)	(0.814)	(0.941)	(0.941)	(0.950)	(0.937)	(0.911)	(0.941)
GETS-IIS-DDD	0.236	1.496	1.614	1.330	1.583	0.902	1.777	1.812	1.898	1.731	1.480	1.777
	(0.592)	(0.927)	(0.941)	(0.903)	(0.937)	(0.812)	(0.957)	(0.959)	(0.966)	(0.953)	(0.925)	(0.957)
GETS-SIS-DDD	-0.112	1.583	1.737	1.315	1.742	0.828	1.969	2.045	2.123	1.891	1.561	1.969
	(0.456)	(0.937)	(0.953)	(0.900)	(0.954)	(0.793)	(0.970)	(0.975)	(0.978)	(0.965)	(0.935)	(0.970)
Ridge, CV	-1.184	-0.891	-0.016	**-2.125**	**-1.991**	**-1.783**	0.429	-1.301	1.867	0.244	-0.575	-0.109
	(0.123)	(0.190)	(0.494)	**(0.021)**	**(0.028)**	**(0.043)**	(0.664)	(0.102)	(0.964)	(0.596)	(0.285)	(0.457)
Lasso, CV	-1.206	-1.540	-0.477	**-2.509**	**-2.040**	**-1.920**	-0.039	-1.336	0.871	-0.413	-1.138	-0.765
	(0.119)	(0.068)	(0.318)	**(0.009)**	**(0.026)**	**(0.033)**	(0.484)	(0.096)	(0.804)	(0.342)	(0.133)	(0.225)
ELNET, CV	-1.212	-1.564	-0.525	**-2.526**	**-2.094**	**-1.924**	-0.095	-1.355	0.831	-0.506	-1.160	-0.869
	(0.118)	(0.065)	(0.302)	**(0.009)**	**(0.023)**	**(0.032)**	(0.462)	(0.093)	(0.793)	(0.309)	(0.128)	(0.196)
Ridge, AIC	-0.822	0.725	0.944	0.077	0.775	-0.119	1.163	0.159	1.421	1.067	0.769	1.152
	(0.209)	(0.763)	(0.823)	(0.531)	(0.777)	(0.453)	(0.873)	(0.563)	(0.917)	(0.852)	(0.776)	(0.870)
Lasso, AIC	0.317	1.168	1.253	0.944	1.260	0.788	1.362	1.299	1.461	1.324	1.177	1.381
	(0.623)	(0.873)	(0.890)	(0.823)	(0.891)	(0.781)	(0.908)	(0.898)	(0.922)	(0.902)	(0.875)	(0.911)
ELNET, AIC	0.215	1.239	1.335	0.987	1.351	0.810	1.464	1.423	1.578	1.417	1.248	1.488
	(0.584)	(0.887)	(0.903)	(0.834)	(0.906)	(0.787)	(0.923)	(0.917)	(0.937)	(0.916)	(0.889)	(0.926)
k-NN	-1.279	-0.914	-0.342	**-2.281**	**-2.973**	**-1.717**	-0.212	-1.587	1.574	-0.413	-0.704	-1.385
	(0.106)	(0.184)	(0.368)	**(0.015)**	**(0.003)**	**(0.049)**	(0.417)	(0.062)	(0.936)	(0.341)	(0.244)	(0.089)
wk-NN	-1.278	-0.995	-0.403	**-2.416**	**-2.951**	**-1.715**	-0.324	-1.568	1.275	-0.563	-0.770	-1.370
	(0.106)	(0.164)	(0.345)	**(0.011)**	**(0.003)**	**(0.049)**	(0.374)	(0.064)	(0.893)	(0.289)	(0.224)	(0.091)
RF	-1.290	**-2.185**	-1.347	**-2.963**	**-2.346**	**-2.288**	-1.349	-1.630	-0.198	-1.266	-1.591	**-2.087**
	(0.104)	**(0.019)**	(0.095)	**(0.003)**	**(0.013)**	**(0.015)**	(0.094)	(0.057)	(0.422)	(0.108)	(0.062)	**(0.023)**
FFNN	-1.082	-0.109	0.555	-1.409	-0.939	-1.228	1.178	-0.994	2.118	0.979	0.076	0.813
	(0.144)	(0.457)	(0.708)	(0.085)	(0.178)	(0.115)	(0.875)	(0.165)	(0.978)	(0.832)	(0.530)	(0.788)
RNN	-0.287	2.101	2.502	0.901	1.828	0.763	2.728	0.979	2.753	2.144	2.067	2.347
	(0.388)	(0.977)	(0.991)	(0.812)	(0.961)	(0.774)	(0.994)	(0.832)	(0.995)	(0.979)	(0.976)	(0.987)
SVR-LIN	-1.201	0.257	0.595	-0.851	-0.048	-0.813	0.885	-1.348	1.427	0.833	0.347	0.995
	(0.120)	(0.600)	(0.722)	(0.201)	(0.481)	(0.212)	(0.808)	(0.094)	(0.917)	(0.794)	(0.634)	(0.836)
SVR-POLY	-0.993	0.336	0.903	-1.035	-0.146	-1.005	1.139	-0.650	1.983	1.422	0.513	1.080
	(0.165)	(0.630)	(0.813)	(0.155)	(0.443)	(0.162)	(0.868)	(0.261)	(0.971)	(0.917)	(0.694)	(0.855)
SVR-RBF	-1.184	-1.091	-0.410	**-2.442**	-1.539	**-1.746**	-0.117	-1.200	0.458	-0.537	-0.931	-0.433
	(0.123)	(0.142)	(0.342)	**(0.011)**	(0.068)	**(0.046)**	(0.454)	(0.120)	(0.675)	(0.298)	(0.180)	(0.334)
SVR-ANOVA	-	1.026	1.109	0.860	1.089	0.617	1.203	1.123	1.317	1.206	1.036	1.229
	-	(0.843)	(0.861)	(0.801)	(0.857)	(0.729)	(0.880)	(0.864)	(0.900)	(0.881)	(0.845)	(0.885)
AR+SVR-POLY	-1.026	-	4.909	-1.691	-0.428	**-1.859**	1.300	-0.779	1.556	1.093	0.826	0.758
	(0.157)	-	(1.000)	(0.051)	(0.336)	**(0.037)**	(0.898)	(0.221)	(0.934)	(0.858)	(0.792)	(0.772)
AR+SVR-RBF	-1.109	**-4.909**	-	**-2.069**	-0.968	**-2.172**	0.425	-1.038	0.886	0.198	-1.674	-0.025
	(0.139)	**(0.000)**	-	**(0.024)**	(0.171)	**(0.019)**	(0.663)	(0.154)	(0.808)	(0.578)	(0.053)	(0.490)
AR+SVR-ANOVA	-0.860	1.691	2.069	-	1.274	-0.362	2.076	0.044	2.816	3.028	1.770	2.330
	(0.199)	(0.949)	(0.976)	-	(0.893)	(0.360)	(0.976)	(0.517)	(0.996)	(0.997)	(0.956)	(0.986)
AR+FFNN	-1.089	0.428	0.968	-1.274	-	-0.927	1.660	-0.977	3.217	1.985	0.556	3.612
	(0.143)	(0.664)	(0.829)	(0.107)	-	(0.181)	(0.946)	(0.169)	(0.998)	(0.971)	(0.708)	(0.999)
AR+RNN	-0.617	1.859	2.172	0.362	0.927	-	1.934	0.247	2.043	1.747	2.045	1.707
	(0.271)	(0.963)	(0.981)	(0.640)	(0.819)	-	(0.968)	(0.597)	(0.975)	(0.954)	(0.975)	(0.950)
Ave. BM	-1.203	-1.300	-0.425	**-2.076**	-1.660	**-1.934**	-	-1.296	1.986	-0.158	-0.815	-0.437
	(0.120)	(0.102)	(0.337)	**(0.024)**	(0.054)	**(0.032)**	-	(0.103)	(0.971)	(0.438)	(0.211)	(0.333)
Ave. Linear	-1.123	0.779	1.038	-0.044	0.977	-0.247	1.296	-	1.743	1.306	0.814	1.443
	(0.136)	(0.779)	(0.846)	(0.483)	(0.831)	(0.403)	(0.897)	-	(0.954)	(0.899)	(0.789)	(0.920)
Ave. Local	-1.317	-1.556	-0.886	**-2.816**	**-3.217**	**-2.043**	**-1.986**	**-1.743**	-	-1.303	-1.220	**-6.427**
	(0.100)	(0.066)	(0.192)	**(0.004)**	**(0.002)**	**(0.025)**	**(0.029)**	**(0.046)**	-	(0.102)	(0.117)	**(0.000)**
Ave. Non-linear	-1.206	-1.093	-0.198	**-3.028**	**-1.985**	**-1.747**	0.158	-1.306	1.303	-	-0.758	-0.332
	(0.119)	(0.142)	(0.422)	**(0.003)**	**(0.029)**	**(0.046)**	(0.562)	(0.101)	(0.898)	-	(0.228)	(0.371)
Ave. AR+	-1.036	-0.826	1.674	**-1.770**	-0.556	**-2.045**	0.815	-0.814	1.220	0.758	-	0.460
	(0.155)	(0.208)	(0.947)	**(0.044)**	(0.292)	**(0.025)**	(0.789)	(0.211)	(0.883)	(0.772)	-	(0.675)
Tot. Ave.	-1.229	-0.758	0.025	**-2.330**	**-3.612**	**-1.707**	0.437	-1.443	6.427	0.332	-0.460	-
	(0.115)	(0.228)	(0.510)	**(0.014)**	**(0.001)**	**(0.050)**	(0.667)	(0.080)	(1.000)	(0.629)	(0.325)	-

Note: This table report test statistics for the modified DM-test of equal forecast accuracy. The null is that the method in row i and column j has equal predictive accuracy. The alternative is that the method in column j is less accurate. p-values reported in parentheses. **Bold** denotes rejections of the null at the 5% level of significance.

A.4 Session info

- R version 3.4.2 (2017-09-28), x86_64-apple-darwin15.6.0
- Locale: C
- Running under: macOS High Sierra 10.13.3
- Matrix products: default
- BLAS: /System/Library/Frameworks/Accelerate.framework/Versions/A/Frameworks/vecLib.framework/Ver
- LAPACK: /Library/Frameworks/R.framework/Versions/3.4/Resources/lib/libRlapack.dylib
- Base packages: base, datasets, grDevices, graphics, methods, parallel, stats, utils
- Other packages: HDeconometrics 0.1.0, MASS 7.3-47, MCS 0.1.3, Matrix 1.2-11, ProjectTemplate 0.8, RColorBrewer 1.1-2, RPushbullet 0.3.1, RSNNS 0.4-10, Rcpp 0.12.15, aTSA 3.1.2, bindrcpp 0.2, broom 0.4.3, caret 6.0-78, colorRamps 2.3, dplyr 0.7.4, forcats 0.2.0, foreach 1.4.4, gets 0.14, ggplot2 2.2.1, ggpubr 0.1.6, ggthemes 3.4.0, glmnet 2.0-13, httr 1.3.1, kernlab 0.9-25, lattice 0.20-35, lmtest 0.9-35, lubridate 1.7.1, magrittr 1.5, mds 0.1.0, neuralnet 1.33, plotflow 0.2.1, purrr 0.2.4, randomForest 4.6-12, readr 1.1.1, readtext 0.50, readxl 1.0.0, reshape 0.8.7, reshape2 1.4.2, rjstat 0.3.0, rpart 4.1-11, rsdmx 0.5-10, sandwich 2.4-0, scales 0.5.0, stringr 1.2.0, strucchange 1.5-1, tibble 1.4.2, tidyr 0.7.2, tidyverse 1.2.1, tikzDevice 0.10-1, urca 1.3-0, vars 1.5-2, xtable 1.8-2, zoo 1.8-0
- Loaded via a namespace (and not attached): CVST 0.2-1, DEoptimR 1.0-8, DRR 0.0.2, Formula 1.2-2, MatrixModels 0.4-1, ModelMetrics 1.1.0, R6 2.2.1, RCurl 1.95-4.10, RcppRoll 0.2.2, SparseM 1.77, TTR 0.23-3, VGAM 1.0-4, XML 3.98-1.9, assertthat 0.2.0, backports 1.1.0, bindr 0.1, bitops 1.0-6, car 2.1-4, cellranger 1.1.0, checkmate 1.8.5, class 7.3-14, cli 1.0.0, codetools 0.2-15, colorspace 1.3-2, compiler 3.4.2, corrplot 0.84, crayon 1.3.4, curl 2.6, data.table 1.10.4-3, ddalpha 1.3.1, digest 0.6.12, dimRed 0.1.0, fBasics 3042.89, fUnitRoots 3042.79, filehash 2.4-1, forecast 8.2, foreign 0.8-69, fracdiff 1.4-2, glue 1.2.0, gower 0.1.2, grid 3.4.2, gtable 0.2.0, haven 1.1.1, hms 0.4.1, igraph 1.1.2, ipred 0.9-6, iterators 1.0.8, jsonlite 1.5, kknn 1.3.1, labeling 0.3, lava 1.5.1, lazyeval 0.2.0, lme4 1.1-13, matrixcalc 1.0-3, maxLik 1.3-4, mgcv 1.8-23, minqa 1.2.4, miscTools 0.6-22, mnormt 1.5-5, modelr 0.1.1, munsell 0.4.3, mvtnorm 1.0-6, nlme 3.1-131, nloptr 1.0.4, nnet 7.3-12, pbkrtest 0.4-7, pillar 1.1.0, pkgconfig 2.0.1, plyr 1.8.4, prodlim 1.6.1, psych 1.7.5, quadprog 1.5-5, quantmod 0.4-12, quantreg 5.33, recipes 0.1.0, rlang 0.1.6, robustbase 0.92-7, rstudioapi 0.7, rvest 0.3.2, sampleSelection 1.0-4, sfsmisc 1.1-1, spatial 7.3-11, splines 3.4.2, stats4 3.4.2, stringi 1.1.5, survival 2.41-3, systemfit 1.1-20, tidyselect 0.2.0, timeDate 3012.100, timeSeries 3042.102, tools 3.4.2, tseries 0.10-42, utf8 1.1.3, withr 2.0.0, xml2 1.1.1, xts 0.10-0, yaml 2.1.14