Aggregate Selection, Data Characteristics and Choice of Optimal Model

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M-competition results are often cited as evidence that complex models do not always produce more accurate forecasts than simple models. Although the results have provided forecasters with informative insights, the results of the competition are generated with an aggregate model for all series instead of an individually selected model for each series. Following Shah (1997), this study introduces an individual model selection procedure for forecasting by employing a multinomial logit (MNL) model to relate best forecast method to data moments (mean, variance, skewness and kurtosis) and selected time-series characteristics (coefficient of variation, number of outliers, step changes, turning points, trend direction, number of observations and ARCH effects). The MNL procedure is trialled on the M3 competition data. Encouragingly, the MNL model based on the Relative GRMSE in particular, is able to indicate the better forecast model reasonably well. Not surprising, results differ by error statistic and higher frequency data are more difficult to forecast. The study is exploratory in nature and another set of data characteristics may be more appropriate for a different series.

1 Introduction

The M-competition forecasting experiments suggest complex models do not always produce more accurate forecasts than simple models and that the forecast performance of each model is dependent on the accuracy measure applied. Although the competition results provide forecasters with informative knowledge in forecasting, the M-competition experiments results are generated mainly via an aggregate model selection, applying the same model to forecast the large collection of series. Fildes (1989, 1992) suggests applying aggregate selection in forecasting is more appropriate as there are gains in forecasting accuracy when applying individually selected models for each series.[1)]

A study by Shah (1997) applies a discriminant analysis approach to select the best forecasting model based on discriminant scores of data characteristics. This shows that an individual selection approach provides more accurate forecasts than an aggregate selected model. This is done by applying discriminant function analysis to a training data set and assigning each series to a particular group of models based on the data features. The data features of a series are then used to estimate the conditional probability of success of a series to determine the 'best' selected model.[2)] The 'best' model is then used to generate forecasts.

In this study, the alternative individual selection approach of Fildes et al (2006) is applied. Instead of applying discriminant function analysis, a multinomial logit (MNL) approach is used to relate data characteristics with out-of-sample forecast accuracy. The results, using 'business and economics' data from the M3-competition suggest the MNL model has the potential to predict the best forecast method to employ based on a set of measurable data characteristics.[3)]

2 Model Selection using Multinomial Logit Model

The approach implicitly assumes the post-sample accuracy of a forecasting method is a function of measurable sample characteristics and a stable relationship exists between data characteristics and better forecasting method. The application of the MNL approach to individually select a model for each series assumes the post-sample forecast accuracy of a forecasting method is a function of measurable sample characteristics that are sufficient in describing the series. This also implies each sample series belongs to one of the forecasting models applied.[4)]

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1) *Fildes (1989) acknowledges the gains of applying individual selection may be small for short lead times.*

2) *The 'best' model is the model generating the highest posterior probability (Shah, 1997).*

3) *The entire database of 3003 mostly business and economic time series was made available to all those interested, via the World Wide Web. Any researcher willing to expend the necessary effort to generate forecasts for all these series was invited to do so. Their forecasts were then e-mailed to Michele Hibon who evaluated the forecast performance using a holdout sample of 6 to 18 observations, depending on the frequency of the data (Ord, 2001). This MNL method has been shown to be successful when applied to daily share prices. (Fildes et al 2006).*

4) *A series belongs to a forecast model if its forecasts generate the lowest out-of-sample forecast errors for the model. However, it does not imply the model is the data generating process of the series.*

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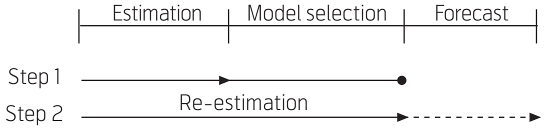

Figure 1 MNL Estimation and Forecast Procedure

To develop selection rules with the multinomial logit, first, two sets of equal observations are left out for each sample series.[5)] Next, forecasts are generated for each shortened series using a selection of forecasting methods, upon which an optimal forecast method is determined based on an error criterion for the first set of omitted observations.[6)] From the forecast results of the first set of omitted observations, a polychotomous variable is then generated for the MNL model that indicates the best forecast model for a series according to the error statistic. That is, the variable equals unity for the best forecast model based on the minimum error statistic and null for the remaining alternative models in the selection. To complete the MNL model specification, data characteristics on each of the sample series are collected for the shortened series. Next, the MNL model is estimated to statistically identify relationships that exist between the best forecast method, data moments and time-series characteristics. In particular, the MNL model is specified as:

$$P(Y_i = j) = \frac{e^{z_i' \beta_j}}{\sum_{m=1}^{J} e^{z_i' \beta_m}}, \quad j = 1, ..., J \qquad (1)$$

where z_i is a vector of series characteristics and j is the index of a corresponding forecast model.

From the MNL model, the best forecast method probabilities are calculated and the forecasting method that generates the highest probability is re-estimated with the shortened series and the first set of omitted observations. This forecast method is then used to forecast the second set of omitted observations. The forecasts for this method are then compared against forecasts generated with the method with the lowest error criterion. The MNL approach is useful as it estimates the conditional probabilities that relate the success of a forecasting model of a series, Y_i, based on collected data characteristics for the series z_i. From the conditional probabilities, forecasts are generated for methods with the greatest posterior probability and compared against the method that generates the lowest error for comparison.

Separate MNL models are estimated for Quarterly, Monthly and Other periodicities. MNL estimation indicates the importance of data series characteristics in determining best forecast method. That is, the MNL can potentially relate certain data characteristic groupings (or data typology) to identify best forecast method by periodicity.

Figure 1 illustrates the MNL procedure as it is applied to the Quarterly and Monthly periodicities. The best fit model is selected on the basis of out-of-sample forecast accuracy for all three periodicities. To select the best forecast model out-of-sample, all observations other than the last 16 and 36 observations of the Quarterly and Monthly periodicity, respectively, are used in estimating each forecast models. The estimated models are then used to forecast the 8 and 18 observations immediately after the estimation period for each periodicity, respectively. Based on the accuracy of the forecasts generated for the 8 and16 observations, a best fit model is chosen by periodicity. This is done by comparing the forecast errors of the 8 (and 18) observations via an error statistic and selecting the model that generates the lowest error by periodicity.

The forecast models by periodicity are then re-estimated with a new estimation period; all observations of each sample are then applied leaving out the last 8 and 16 observations by periodicity. The re-estimated models are then used to generate forecasts for the remaining 8 and 16 observations. The forecast accuracy of the models is then compared from which a best model is selected.

Fildes (1989) suggests gains in forecasting accuracy using individual model selection are limited. Fildes (1989) suggests there are small gains applying the procedure to short time-series and the procedure only outperforms aggregate model selection for longer time-series. The study also tests this proposition by comparing forecasts generated from applying the individually-selected MNL procedure against two aggregate-selected methods. The first method is to employ the forecast model that generates lowest average error for all sample series by periodicity.[7)] The second method is to employ the forecast model that

5) *The number of observations left out in each series depends on the periodicity. The number left out for each periodicity is twice the number for each periodicity applied by Hibon and Makridakis (2000). The left-out observations are used for evaluating out-of-sample forecasting.*

6) *The first set of omitted observations is half the total number of omitted observations.*

7) *The aggregate selection method is commonly adopted by practitioners as a practical method for forecasting a large number of series (Fildes, 1989).*

is most frequently selected by the MNL procedure by periodicity. The forecast errors of the individual and aggregate selected methods are compared to determine which method of selection is better.

Data Characteristics Applied

To enable MNL model estimation, data on series characteristics are collected for two sub-samples. The first sub-sample is for the shortened series and the second is for the shortened series including the first set of omitted observations. Of the characteristics described by Collopy and Armstrong (1992), Shah (1997), Fildes et al (1998) and Meade (2000), the mean, median, variance, skewness, kurtosis, step changes, turning points, number of outliers, coefficient of variation, presence of ARCH effects, trend direction and the presence of an extreme last observation are calculated.[8] An Outlier is defined as an observation that exceeds 3 standard deviations of a series mean. Step changes and turning points are as defined by Shah (1997). A turning point captures oscillating behaviour of a series X_t while a step change identifies structural breaks of a series. That is, a turning point is any observation in a series ($1 < t < T$) for which $X_{t-1} < X_t$ and $X_{t+1} < X_t$ or $X_{t-1} > X_t$ and $X_{t+1} > X_t$. A step change occurs in a series when the absolute difference of an observation and its lagged mean $\bar{X}_{t-1}$ exceed twice the lagged standard deviation of the series s_{t-1}, viz.,

$$| X_t - \bar{X}_{t-1} | > 2s_{t-1}. \quad t = 1, ..., T$$

A series with a relatively large number of structural breaks will exhibit relatively many step changes. Trend direction and the presence of an extreme last observation are as defined by Meade (2000). Trend direction is a binary variable that determines whether the basic and recent trend of a series is similar in direction. The basic trend is the gradient of the regression of a series against time containing all observations, while the recent trend is the gradient of a similar regression performed with only the last six observations. The trend variable value equals unity when the basic and recent trend of a series is in the same direction and zero otherwise. An extreme last observation is any last observation that is greater than 90 % of the largest observation, $X_T > 0.9 \max(X_1, ..., X_{T-1})$, or is less than 110 % of the smallest observation, $X_T < 1.1 \min(X_1, ..., X_{T-1})$. Hence, this variable has the value unity in the presence of an extreme last observation and zero otherwise. The variable for the presence of an ARCH effect is a binary variable that is determined by the result of Engle's (1982) Lagrange multiplier (LM) test with a one-period lag. The variable has the value unity when an ARCH effect is detected by the LM test and zero otherwise. The LM test for ARCH is applied to the residuals of the best fitting ARIMA model determined by the lowest AIC.

Models Employed

Exponential smoothing and ARMA-based models are employed as they consistently perform well in the M-competition of Fildes (1992), Makridakis et al (1993), Fildes et al (1998) and Makridakis and Hibon (2000). Exponential smoothing methods assume a series is comprised of systematic and random variation that can be described by level and trend (Meade 2000). Smoothing models considered are Holt, Holt-D, Holt-Winters (Holt-W) and simple exponential smoothing (SES).[9] An alternative smoothing model, a non-parametric version of Holt's linear trend, Grambsch and Stahel's (1990) Robust Trend (RT), is also estimated. RT is a good basis for comparison as it is median-based and insensitive to outliers. ARMA-based models are ARARMA and ARIMA (p, d, q). Parzen's (1982) ARARMA is a long-memory process that uses a best fit AR model, according to the Akaike Information Criteria (AIC), as a filter to difference series prior to estimating the best fitting ARMA model (by the AIC).[10] The ARIMA (p, d, q) model is chosen as the M3 data may be non-stationary. Cogent application of the ARIMA model assumes the M3-competition series are not seasonally influenced or affected by other factors. In this situation seasonal ARIMA or ARMAX models are most suitable. To select a best fit ARIMA (p, d, q) model, Meade's (2000) procedure is employed. First, the number of differences required to make the series stationary is determined by applying the Geweke and Porter-Hudek (GPH 1983) procedure. The GPH procedure estimates real number differences for an autoregressive fractionally integrated moving average process. For the ARIMA model the GPH value is converted to an integer by the rule, when $d < 0.5$ then $d = 0$, otherwise d equals the integer part of $d + 0.5$. After differencing, alternative ARIMA models are applied by a grid search of up to 5 lags, generating 25 ARIMA models per series. From these estimated models, a best fitting ARIMA model is chosen via the AIC statistic. From 7 alternative models, a best fit model is selected on the basis of out-of-sample fore-

8) *Other data characteristics described by these studies are not collected as they either describe similar series features or are highly correlated with other characteristics.*

9) *A description of exponential smoothing models is given by Gardner and McKenzie (1988) and Gardner (2006).*

10) *While Parzen (1982) uses an autoregressive transfer function (CAT) criterion to select a best AR filter, he notes the selection of the filter by CAT and AIC are similar.*

cast accuracy for a corresponding forecasting period. The out-of-sample forecast period uses the last 8, 18, and 8 observations,respectively, for the Quarterly, Monthly and other series. These observations are set aside prior to model estimation. Choice of best forecast method by periodicity is based on the geometric root mean squared error (GRMSE; Fildes 1992) and root mean squared error (RMSE) forecast error statistics. Estimation by method begins at observation 10 to allow a maximum 5 and 3 period lags for the ARIMA and ARARMA models, respectively. Forecasts are generated for best models by method. Holt-D, Holt-W and RT models have a fixed lag length and do not require grid search to select the best model.[11)] Grid search for optimal lag length is based on the least AIC statistic. The study findings suggest the MNL model has potential to a priori indicate the best forecast method based on a set of measurable data characteristics, rather than relying on forecaster judgement. The MNL-based procedure is trialled on the M3-competition data.

Errors Employed

The errors applied to select the best fitting model are relative measures, namely the relative GRMSE (RelGRMSE) and the relative MAE (RelMAE). Relative errors are calculated by dividing the error statistic by another corresponding error statistic calculated using a benchmark method of forecasting. The benchmark model applied here is the random walk model.

The RelGRMSE is the preferable measure as Fildes and Ord (2002) argue the GRMSE as it is insensitive to scale changes. Also, Armstrong and Collopy (1992) consider the GRMSE more reliable as it is sensitive to small changes but not affected by outliers. The RelMAE statistic is calculated for comparison. To calculate the RelGRMSE, first the mean squared error is estimated by

$$MSE_{i,h,j} = \sum_{1}^{S} \left(A_{h,j} - F_{i,h,j}\right)^2 S^{-1},$$

where $F_{i,h,j}$ and $A_{h,j}$ are the forecast and actual for method i, horizon h and series j, at horizon h for series j. S is the length of forecast period. $RMSE_{i,h,j}$ is the root of the $MSE_{i,h,j}$, viz.,

$$RMSE_{i,h,j} = \sqrt{MSE_{i,h,j}}.$$

An advantage of the GRMSE is that it is scale-invariant. The error statistic is

$$GRMSE = \left(\prod_{1}^{n} \varepsilon_{i,h,j}\right)^{\frac{1}{2n}}$$

where ε_i, h, j is the forecast error for method i for horizon h using series j and $n = S - h + 1$ is the number of effective data points.

To calculate the RelMAE, first the mean absolute error is estimated by

$$MAE_{i,h,j} = \sum_{1}^{S} |A_{h,j} - F_{i,h,j}| S^{-1}$$

then the RelMAE is calculated as RelMAE = MAE/MAE_b where MAE is the mean absolute error of tested model and MAE_b is the mean absolute error of the benchmark model.

2 Data

M3-competition data are obtained from the Institute of Forecasters website (www.forecasters.org). The data set contains 3003 series comprised of 828 Microeconomic, 519 Industry, 731 Macroeconomic, 308 Financial, 413 Demographic and 204 Other series.[12)] These M3-competition series are of Annual, Quarterly, Monthly and Other periodicity.[13)] Table 1 summarises these data by source and periodicity. The study focus is the ‘Business and Economic’ component of the data set. Hence, demographic data is omitted and 2590 series remain. Table 2 further summaries these data by series length and periodicity. Annual and Quarterly data are mostly short series, while Monthly and Other data are comprised of typically longer time-series. M3 observations are strictly positive with no additional information provided by the Institute.

A minimum length of 30 observations for estimation prior to out-of-sample forecasting is required. Following Shah (1997) and Makridakis and Hibon (2000) two adjacent out-of-sample forecasts of 6, 8, 18 and

11) *Linear, no trend and non-seasonal Holt and Holt-W models are considered. Holt-D is the exponentially smoothed Holt model. Parameters are estimated and not fixed arbitrarily.*

12) *Other period data consists mainly of gas, water and telecommunications industry series. The M-Competition is an empirical study concerned with (mostly) post-sample forecasting accuracy of extrapolative (time series) methods. The study is organised as a ‘forecasting competition’ in which experts analysed and forecast real-life time-series. The competition expands on the earlier work of Makridakis and Hibon (1979) based on suggestions made at a meeting of the Royal Society (Makridakis et al, 1982). Stylized outcomes from this and subsequent competitions are summarized by Makridakis and Hibon (2000). In particular, statistically simpler models perform better than complex methods; ranking of competing methods varies across accuracy measures; combining forecasts perform best; and accuracy depends on the forecast horizon.*

13) *‘Other’ means the series’ periodicity is unknown or is not of annual, quarterly or monthly periodicity.*

Periodicity	Micro	Industry	Macro	Finance	Demo	Other	Total
Annual	146	102	83	58	245	11	645
Quarterly	204	83	336	76	57	0	756
Monthly	474	334	312	145	111	52	1428
Other	4	0	0	29	0	141	174
Total	**828**	**519**	**731**	**308**	**413**	**204**	**3003**

Note: Micro is to microeconomic data; Macro is macroeconomic data; Demo is demographic data.

Table 1 M3 Competition Data Series by Source and Periodicity

8 observations for each Annual, Quarterly, Monthly and Other series are required. Hence, a minimum series length of 42, 46, 66 and 46 observations are required for Annual, Quarterly, Monthly and Other series, respectively. This procedure ensures an estimation period of 30 observations is used to estimate model parameters. That is, all series containing at least 30 observations, excluding the last 6 (Annual), 8 (Quarterly), 18 (Monthly) and 8 (Other) observations, respectively are used to initialise the models. Forecasts are made for the post-estimation period. An additional observation is added and forecasts revised. The forecast errors by forecast model are calculated with observations set aside.

Table 3 reports the number of Business and Economics series remaining after satisfying the minimum length criterion by periodicity. Imposing the required series minimum length reduces the sample further from 2590 to 1286 series. Discarded series are mainly Annual and Quarterly Business and Economics data. All annual series are discarded, while about 295 quarterly and 326 monthly series are also discarded from the various categories.

To further reduce the sample, all the Other series are also removed from the sample. This is done as the exact periodicity of each Other series is unknown.[14) This reduces the number of series from 1286 to 1112 series.

A summary of sample statistics of the Quarterly and Monthly M3-competition sample series are presented in Table 4 and Table 5. Average series standard deviations by periodicity are at 761.93 (Quarterly) and 997.66 (Monthly), respectively and indicates the Monthly series are more volatile than the Quarterly series. The average series coefficients of variation (CV) exhibits a similar pattern, with sample values of 0.17 (Quarterly) and 0.22 (Monthly) respectively. The average sample values for the runs, step changes and presence of autoregressive conditional heteroscedasticity (ARCH) effect statistics follow a similar pattern in terms of their relative magnitude by series periodicity. Further, these data are positively skewed due to the non-negativity of sample observations. The tables show the Monthly series have lower skewness (4.80) and kurtosis (0.11) than the Quarterly series. Another difference is that, on average, Quarterly series have fewer turning points (15.08) than the Monthly (15.84) series. The average occurrence of series of an ARCH effect for Quarterly (0.12) series is dissimilar to that of a Monthly (0.21) series. Finally, the Monthly series has a lower average incidence of outliers (22.55) when compared to Quarterly (30.62) series.

Periodicity	Least Observations	Most Observations
Annual	14	41
Quarterly	16	63
Monthly	48	126
Other	63	96

Table 2 Business and Economic Data Series by Length and Periodicity

Following Fildes (1992), strength of trend and randomness of each series by periodicity are analysed. The strength of trend is measured by the absolute

Periodicity	Micro	Industry	Macro	Finance	Other	Total
Quarterly	0	60	32	29	0	121
Monthly	197	334	309	128	23	991
Other	4	0	0	29	141	174
Total	**247**	**394**	**341**	**186**	**164**	**1286**

Table 3 Business and Economic Data Series by Source and Periodicity

14) *The Other series may be a mixture of weekly series with intra-day series. The series are removed as any interpretation of the results for the Other series may be erroneous.*

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Characteristic	Mean	Std Dev	Skewness	Kurtosis	Minimum	Maximum
Mean	4832.53	1252.43	0.44	3.81	938.84	9807.79
Std Dev	761.93	473.00	1.63	7.17	39.10	3165.54
Skewness	35.50	40.09	1.92	6.51	-3.14	226.08
Kurtosis	-0.61	0.81	1.76	7.57	-1.73	4.34
Outliers	30.62	9.78	-1.77	4.94	0.00	36.00
Step Change	0.93	1.23	1.54	5.33	0.00	6.00
Turn Point	15.08	7.10	0.43	3.55	0.00	36.00
Runs	15.23	6.51	0.39	3.92	1.00	36.00
CV	0.17	0.11	1.68	6.81	0.01	0.73
ARCH	0.12	0.32	2.40	6.78	0.00	1.00

Note: Std Dev is standard deviation; Step Change and Turn Point are number of step changes and turning points, respectively; Outlier is outliers larger than 3 standard deviations; CV is coefficient of variation and ARCH is a binary variable = 1 for an ARCH effect and otherwise = 0. ARCH is determined from the residuals of the lowest AIC ARIMA model.

Table 4 Quarterly Data Series Characteristics – 416 Series

Characteristic	Mean	Std Dev	Skewness	Kurtosis	Minimum	Maximum
Mean	4840.62	1712.14	1.43	9.55	1187.82	18359.50
Std Dev	997.66	849.89	6.74	95.44	57.75	16219.70
Skewness	24.02	40.22	4.57	35.87	-3.80	480.87
Kurtosis	0.07	1.79	4.91	47.02	-1.90	23.91
Outliers	22.55	10.46	-1.02	2.48	0.00	30.00
Step Change	1.05	0.85	0.43	2.54	0.00	4.00
Turn Point	15.84	5.17	-0.84	3.37	0.00	27.00
Runs	16.72	5.00	-0.92	3.55	1.00	27.00
CV	0.22	0.16	1.57	6.34	0.02	1.13
ARCH	0.21	0.40	1.45	3.10	0.00	1.00

Note: Std Dev is standard deviation; Step Change and Turn Point are number of step changes and turning points, respectively; Outlier is outliers larger than 3 standard deviations; CV is coefficient of variation and ARCH is a binary variable = 1 for an ARCH effect and otherwise = 0. ARCH is determined from the residuals of the lowest AIC ARIMA model.

Table 5 Monthly Data Series Characteristics – 1317 Series

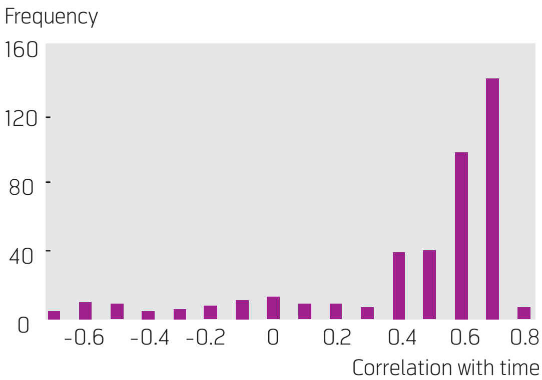

Figure 2a Quarterly Data Series Temporal Correlation

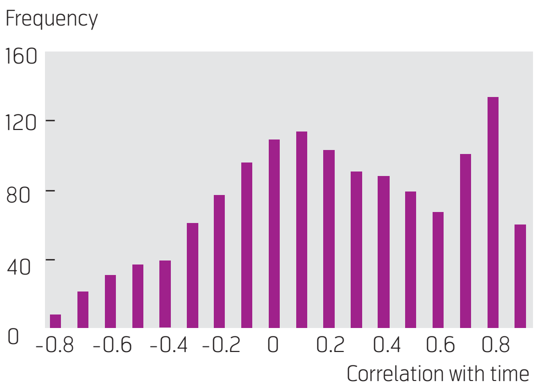

Figure 2b Monthly Data Series Temporal Correlation

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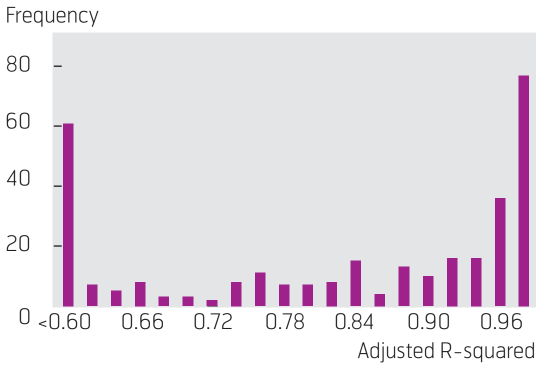

Figure 3 Quarterly Data Series Randomness

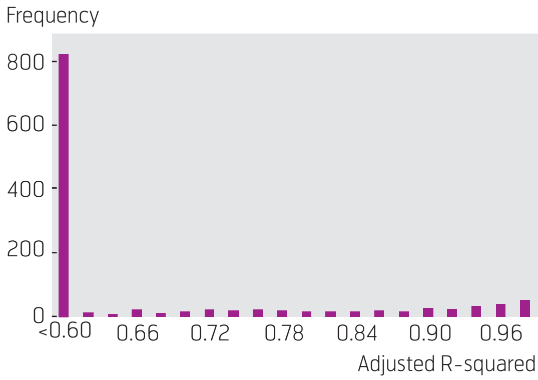

Figure 4 Monthly Data Series Randomness

value of the correlation of (outliers removed) with a time trend. A measure of randomness is provided by the regression:

$$X'_t = \alpha + \beta t + \delta_1 X'_{t-1} + \delta_2 X'_{t-2} + \delta_3 X'_{t-3}, \quad (1)$$

where X_t' denotes a series X_t with outliers removed and $\bar{R}_2$ measures the variation explained by the model. High $\bar{R}^2$ indicates little randomness in the data. Figure 1 through to Figure 4 show strength of trend by series periodicity. Figure 1 indicates the Quarterly series are mostly positively correlated with time. Approximately 348 Quarterly series report positive correlations, upward trending (see Figure 2). Further, Figure 2 appears to suggest a large number of Monthly series (837 of 1317) are positively correlated with time or upward sloping. However, half of these series have a sample correlation coefficient less than 0.6.

The estimated $\bar{R}^2$ of (1) by periodicity are contained in Figure 3 and Figure 4. Most Quarterly series (Figure 6) exhibit little randomness, viz., only 61 (of 416) series show randomness, while Figure 7 indicates most Monthly series are highly random.

Results

The results for the logit model are estimated with the RT as a base model. Other models as the base, such as the SES and the ARARMA were applied, but as the results are relatively similar; the logit results for those models are not presented in this paper.[15)]

For Quarterly data, the results for the MNL model based on the RelGRMSE in Table 3 and Table 4 suggest that ARIMA forecasts are more accurate (relative to RT) when there are less step changes. Holt is better (relative to RT) the less skewed is a series, when there are fewer turning points and when an extreme last observation is present. Holt-W forecasts are more accurate (relative to RT) when a series has no trend and when a series is finance-related. SES is better (relative to RT), the lower is the series skewness, and when there is a lower number of step changes.

Table 9 reveals that the MNL model correctly predicts the best forecast method for 52.9 % of the 121 Quarterly series. In particular, the MNL correctly predicts the ARARMA (50.0 %), ARIMA (54.8 %), Holt (60.0 %), Holt-D (57.1 %) and SES (69.2 %) methods, respectively. However, the MNL model is unable to accurately predict Holt-W or RT as the best forecast method.

MNL model results based on the RelMAE reported in Table 8 and Table 9, indicate the ARIMA is more likely the better model (relative to RT) the higher the number of turning points and when the series has no trend and when an extreme last observation occurs. The Holt model forecasts better than an RT for a series with a lower mean, higher standard deviation and when a series contains a higher number of outliers. The Holt-D forecasts better than an RT for a series with a higher number of turning points. The Holt-W is the better model (relative to the RT) when a series does not exhibit a trend. Finally, SES is preferred to RT when there is a higher number of outliers present in the series and when a series does not exhibit a trend. Table 11 shows the MNL model based on the RelMAE is as effective in indicating the better method as the RelGRMSE model by correctly predicting the best forecast method for 51.2 % of the series. The RelMAE based MNL model correctly predicts the ARIMA (57.1 %), Holt (70.6 %), Holt-W (53.3 %) and SES (55.6 %) as the best forecast method. The RelMAE model is unable to predict the ARARMA, Holt-D and RT models.

15) *These results are made available upon request to the authors.*

Variable	ARARMA	ARIMA	Holt	Holt-D	Holt-W	SES
Mean	0.0010	0.0001	-0.0002	0.0002	0.0014	0.0010
	(0.0006)	(0.0004)	(0.0006)	(0.0005)	(0.0008)	(0.0005)
Std Dev	-0.0015	0.0003	0.0011	0.0008	-0.0023	-0.0012
	(0.0019)	(0.0015)	(0.0024)	(0.0021)	(0.0022)	(0.0020)
Skewness	-0.0355	0.0056	-0.0692*	-0.0870	-0.0369	-0.0638*
	(0.0246)	(0.0192)	(0.0292)	(0.0560)	(0.0264)	(0.0300)
Kurtosis	1.9092	1.7900	2.2778	-4.1395	1.3707	2.3552
	(1.9260)	(1.9217)	(2.0068)	(5.2648)	(2.0389)	(1.8655)
Step Chg	-57.3408	-64.8805*	-23.5633	13.0677	-37.1885	-54.3395*
	(29.9556)	(26.0321)	(29.9974)	(52.9152)	(34.3339)	(24.3330)
Turn Pt	-4.9791	3.3595	-7.1395*	-2.0426	2.5018	2.4726
	(4.1214)	(3.0302)	(3.4628)	(4.0439)	(4.1594)	(3.4148)
Outliers	0.6947	4.3556	6.5023	0.4408	2.0495	1.5566
	(4.8756)	(4.7137)	(5.3198)	(6.6048)	(5.1511)	(5.0636)
CV	14.7928	11.8860	5.4291	-6.4535	19.3206	9.4581
	(12.5239)	(11.8237)	(13.1629)	(20.9693)	(13.5469)	(13.8305)
ARCH	0.5634	-0.0691	2.5143	0.1673	0.2074	0.9583
	(2.2497)	(2.0010)	(2.2775)	(2.1654)	(2.8474)	(2.1411)
Extreme	0.1893	1.0872	4.1449*	1.0715	-1.1307	-0.8433
	(0.9809)	(0.9779)	(1.6752)	(1.0835)	(1.5601)	(0.9773)
Trend	-0.7920	-1.3298	-0.6963	-1.0086	-3.1921*	-0.6165
	(1.1804)	(0.9201)	(1.1743)	(2.1553)	(1.3526)	(1.0061)
Discont	1.5687	1.5021	-0.1194	-1.5123	3.5487	1.3423
	(1.4935)	(1.3428)	(1.3260)	(2.0833)	(1.8781)	(1.3797)
Obs	-0.0588	-0.0999	-0.0778	-0.0544	-0.1383	-0.0379
	(0.1079)	(0.1063)	(0.1157)	(0.1034)	(0.1188)	(0.1113)
Dummy	1.6872	-0.4442	0.6854	1.4189	-2.9126*	-1.5034
	(1.9669)	(1.1818)	(1.2556)	(3.6660)	(1.4517)	(1.2243)

Note: Std Dev is the standard deviation; Step Change is step change to observations ratio; Turn Point is turning point to observations ratio; Outlier is outliers larger than 3 standard deviations; CV is the coefficient of variation; ARCH = 1 is for an ARCH effect, = 0 otherwise; Extreme = 1 is for presence of extreme last observations, = 0 otherwise; Trend = 1 when basic trend is similar to recent trend, = 0 otherwise; Discont = 1 when there are discontinues in the series, = 0 otherwise; Obs is number of sample observations. ARCH is determined from residuals of the lowest AIC ARIMA model. Dummy = 1 when series is not finance-related, = 0 otherwise. Likelihood ratio for this model against a model with a constant is 0.312. Standard deviations are in parentheses. * is significant at 5 %.

Table 6 Quarterly Data Series MNL Model Coefficient Estimates – RelGRMSE

Method	Correctly Predicted	Actual	Percent Correct
ARARMA	8	16	50.0
ARIMA	17	31	54.8
Holt	9	15	60.0
Holt-D	8	14	57.1
Holt-W	2	10	20.0
RT	2	9	22.2
SES	18	26	69.2
Total	**64**	**121**	**52.9**

Table 7 Quarterly Data Series Prediction – RelGRMSE

When the MNL models based on the RelGRMSE and RelMAE are applied to the Monthly series, results for the MNL models are inconclusive. This is because the MNL models based on the RelGRMSE and RelMAE for the monthly series shown in Table 10 and Table 12 generate very low R^2, 0.040 and 0.057, respectively. This suggests the applied MNL models for the monthly series are unable to capture a relationship between the data characteristics and forecast selection. The failure of the MNL models may be due to the sample structure. The majority of the monthly series in the sample exhibit a low correlation with time (shown in Figure 3) and a high randomness (shown in Figure 4). This indicates the majority of

Variable	ARARMA	ARIMA	Holt	Holt-D	Holt-W	SES
Mean	-0.0002	-0.0010	-0.0017*	-0.0004	-0.0003	0.0003
	(0.0001)	(0.0006)	(0.0008)	(0.0006)	(0.0006)	(0.0006)
Std Dev	0.0010	0.0025	0.0092*	0.0031	0.0018	-0.0018
	(0.0004)	(0.0018)	(0.0042)	(0.0021)	(0.0023)	(0.0025)
Skewness	0.0184	0.0727	-0.0053	0.0594	0.0404	-0.1008
	(0.0062)	(0.0511)	(0.0578)	(0.0508)	(0.0523)	(0.0795)
Kurtosis	-0.1004	0.9943	3.6431	3.0551	3.9851	3.8731
	(0.1101)	(2.2129)	(2.4826)	(2.2107)	(2.2764)	(2.1986)
Step Chg	2.7665	-46.6509	-76.2555	-41.3197	-44.9035	-50.8224
	(7.3943)	(44.5735)	(54.8960)	(46.3412)	(48.4636)	(43.5470)
Turn Pt	-0.4743	14.1288*	-4.3847	10.3893*	7.1009	0.1986
	(1.0162)	(4.4812)	(7.4507)	(4.0200)	(4.4501)	(4.7634)
Outliers	-1.2256	0.7153	11.5416*	8.4026	5.3175	9.6931*
	(0.9231)	(4.3729)	(4.9132)	(4.2941)	(4.3520)	(4.7827)
CV	-6.4475	-3.9395	-23.4732	-2.2032	-5.8940	14.4738
	(2.2918)	(7.6317)	(20.0046)	(9.9925)	(10.3057)	(10.0523)
ARCH	0.4341	-3.3383	2.4244	-2.5311	-2.6018	-2.1322
	(0.2966)	(2.6769)	(2.7594)	(2.5218)	(2.5602)	(2.9782)
Extreme	0.3458	3.0100*	2.4145	1.0842	2.6689	-0.5980
	(0.3266)	(1.1497)	(1.5252)	(1.1092)	(1.6705)	(1.3507)
Trend	0.0839	-4.1178*	-1.8888	-3.6818	-4.2297*	-3.3925*
	(0.5006)	(1.8966)	(1.6337)	(1.9632)	(1.9666)	(1.6699)
Discont	0.1215	0.4020	-1.1130	-0.8864	0.7173	-0.2089
	(0.2963)	(1.3333)	(1.4786)	(1.2921)	(1.3761)	(1.2430)
Obs	0.0185	-0.0470	-0.0059	-0.1255	-0.0484	-0.0317
	(0.0115)	(0.1098)	(0.1301)	(0.1128)	(0.1169)	(0.1071)
Dummy	0.9473	-0.3615	1.8619	-3.1565	-1.2477	-1.6594
	(0.4850)	(1.9267)	(1.6790)	(1.7931)	(1.7924)	(1.3985)

Note: Std Dev is the standard deviation; Step Change is step change to observations ratio; Turn Point is turning point to observations ratio; Outlier is outliers larger than 3 standard deviations; CV is the coefficient of variation; ARCH = 1 is for an ARCH effect, = 0 otherwise; Extreme = 1 is for presence of extreme last observations, = 0 otherwise; Trend = 1 when basic trend is similar to recent trend, = 0 otherwise; Discont = 1 when there are discontinues in the series, = 0 otherwise; Obs is number of sample observations. ARCH is determined from residuals of the lowest AIC ARIMA model. Dummy = 1 when series is not finance-related, = 0 otherwise. Likelihood ratio for this model against a model with a constant is 0.344. Standard deviations are in parentheses. * is significant at 5 %.

Table 8 Quarterly Data Series MNL Model Coefficient Estimates – RelMAE

the monthly series do not exhibit sufficient clustering for the MNL method to be implemented.

The poor performance of the MNL model by error statistic is further highlighted in Table 11 and Table 13. Table 11 shows that the MNL model is unable to predict the best forecast model for most of the Monthly series. In particular, the MNL model is only able to correctly predict the better model in 30.5 % (991 Monthly series) of cases. Further, the MNL model only correctly predicts the ARIMA (87.0 % accuracy) model, but unable to correctly predict the ARARMA, Holt, Holt-D, Holt-W, RT and SES models. Table 13 also shows poor predictive performance

Method	Correctly Predicted	Actual	Percent Correct
ARARMA	8	21	38.1
ARIMA	12	21	57.1
Holt	12	17	70.6
Holt-D	8	17	47.1
Holt-W	8	15	53.3
RT	4	9	44.4
SES	10	18	55.6
Total	62	121	51.2

Table 9 Quarterly Data Series Prediction – RelMAE

Variable	ARARMA	ARIMA	Holt	Holt-D	Holt-W	SES
Mean	-0.0001	-0.0001	-0.0002	-0.0002	-0.0003*	-0.0003*
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Std Dev	0.0008	0.0005	0.0010*	0.0010*	0.0011*	0.0013*
	(0.0005)	(0.0004)	(0.0004)	(0.0004)	(0.0004)	(0.0005)
Skewness	0.0169*	0.0158*	0.0190*	0.0184*	0.0203*	0.0111
	(0.0059)	(0.0059)	(0.0059)	(0.0061)	(0.0059)	(0.0060)
Kurtosis	0.0177	-0.0140	-0.1659	0.0292	0.0214	-0.2750
	(0.0878)	(0.0674)	(0.1022)	(0.0749)	(0.0681)	(0.1753)
Step Chg	5.9150	11.5641	10.7506	-2.1901	12.7795	5.3374
	(7.3679)	(5.9741)	(7.6753)	(6.7018)	(7.0577)	(7.4042)
Turn Pt	-1.3548	0.4174	1.0993	-0.8078	0.1322	-1.0124
	(1.0218)	(0.8368)	(1.0936)	(0.8702)	(1.0010)	(0.9554)
Outliers	-0.1550	0.3833	-0.4650	0.2884	0.7190	1.3436
	(0.9060)	(0.7696)	(1.0318)	(0.8982)	(1.0828)	(0.9714)
CV	-3.1545	-0.3499	-4.6080	-1.8937	-3.8416	-5.8698*
	(2.5199)	(1.7235)	(2.3919)	(2.1175)	(2.4389)	(2.5241)
ARCH	0.4560	0.2051	0.2795	0.1732	0.0612	-0.1488
	(0.3062)	(0.2592)	(0.3181)	(0.3072)	(0.3248)	(0.3162)
Extreme	0.3687	-0.0972	0.1079	0.1966	0.3502	0.2479
	(0.3355)	(0.2966)	(0.3593)	(0.3347)	(0.3458)	(0.3216)
Trend	-0.3966	-0.2673	-0.3071	-1.0122	-0.2102	0.0579
	(0.4611)	(0.4157)	(0.5275)	(0.5365)	(0.4973)	(0.4466)
Discont	0.0455	0.2247	0.2380	0.3504	0.4777	0.2906
	(0.3031)	(0.2488)	(0.3263)	(0.2905)	(0.2972)	(0.2882)
Obs	-0.0015	-0.0071	-0.0099	-0.0015	-0.0122	0.0000
	(0.0118)	(0.0092)	(0.0134)	(0.0110)	(0.0131)	(0.0120)
Dummy	1.0104*	0.6983	1.6442*	0.5778	0.8731	0.8890
	(0.4593)	(0.4401)	(0.5028)	(0.4883)	(0.5003)	(0.4673)

Note: Std Dev is the standard deviation; Step Change is step change to observations ratio; Turn Point is turning point to observations ratio; Outlier is outliers larger than 3 standard deviations; CV is the coefficient of variation; ARCH = 1 is for an ARCH effect, = 0 otherwise; Extreme = 1 is for presence of extreme last observations, = 0 otherwise; Trend = 1 when basic trend is similar to recent trend, = 0 otherwise; Discont = 1 when there are discontinues in the series, = 0 otherwise; Obs is number of sample observations. ARCH is determined from residuals of the lowest AIC ARIMA model. Dummy = 1 when series is not finance-related, = 0 otherwise. Likelihood ratio for this model against a model with a constant is 0.04. Standard deviations are in parentheses. * is significant at 5 %.

Table 10 Monthly Data Series MNL Model Coefficient Estimates – RelGRMSE

Method	Correctly Predicted	Actual	Percent Correct
ARARMA	7	113	6.2
ARIMA	248	285	87.0
Holt	0	94	0.0
Holt-D	6	124	4.8
Holt-W	2	107	1.9
RT	0	128	0.0
SES	39	140	27.9
Total	**302**	**991**	**30.5**

Table 11 Monthly Data Series Prediction – RelGRMSE

for the MNL model based on the RelMAE. The RelMAE-based model correctly predicts the better model only 30.0 % of (991) Monthly series. In particular, RelMAE results show the MNL model can only successfully predict the ARIMA (with 52.0 % accuracy) model. However, the RelMAE-based model is unable to predict ARARMA, Holt, Holt-D, Holt-W, RT and SES models. The poor predictive ability for the monthly series when compared against the MNL model for the quarterly series suggests the MNL individual selection model works well for a non-random collection of series.

Variable	ARARMA	ARIMA	Holt	Holt-D	Holt-W	SES
Mean	-0.0004*	-0.0003*	-0.0006*	-0.0003*	-0.0005*	-0.0003
	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
Std Dev	0.0017*	0.0012*	0.0016*	0.0011*	0.0011	0.0002
	(0.0005)	(0.0005)	(0.0005)	(0.0005)	(0.0006)	(0.0007)
Skewness	0.0191*	0.0197*	0.0231*	0.0207*	0.0182*	0.0172*
	(0.0059)	(0.0059)	(0.0060)	(0.0064)	(0.0064)	(0.0059)
Kurtosis	0.0557	-0.0329	-0.1282	0.1228*	0.0436	0.0538
	(0.0964)	(0.0731)	(0.1311)	(0.0626)	(0.0712)	(0.0983)
Step Chg	-10.2734	5.1973	-6.7841	17.7368*	3.1816	-10.9529
	(7.7405)	(6.8393)	(9.0301)	(6.8659)	(7.6304)	(7.7352)
Turn Pt	-1.0546	-1.9393	-1.0265	-0.4644	-0.2459	-1.5262
	(1.1160)	(0.9971)	(1.1087)	(1.0449)	(1.0752)	(1.0563)
Outliers	0.8795	1.3612	1.3047	1.4499	1.0978	1.2335
	(0.9636)	(0.7921)	(1.1698)	(0.8245)	(0.9093)	(0.9449)
CV	-6.8054*	-0.7753	-5.4698	-1.4191	-3.1188	-1.3374
	(2.5132)	(1.9993)	(2.9338)	(2.0755)	(2.2704)	(3.1638)
ARCH	0.1309	0.1781	0.4462	0.2243	0.1967	0.2246
	(0.3602)	(0.3192)	(0.3857)	(0.3277)	(0.3375)	(0.3396)
Extreme	0.7915	-0.1698	0.0875	-0.0414	-0.1817	-0.1734
	(0.3488)	(0.3152)	(0.3965)	(0.3312)	(0.3406)	(0.3270)
Trend	1.0056	0.8233	0.1380	-0.2786	0.3824	1.0859
	(0.6377)	(0.6076)	(0.8691)	(0.6708)	(0.6580)	(0.6578)
Discont	-0.0868	0.0919	0.1478	0.0993	0.3314	-0.0726
	(0.3291)	(0.2900)	(0.3615)	(0.3011)	(0.3055)	(0.3207)
Obs	0.0112	0.0073	0.0104	-0.0117	0.0080	0.0152
	(0.0123)	(0.0102)	(0.0147)	(0.0106)	(0.0112)	(0.0130)
Dummy	0.8513	0.2668	0.6418	0.8541	1.3803*	0.6430
	(0.5285)	(0.5138)	(0.6155)	(0.5222)	(0.5006)	(0.5493)

Note: Std Dev is the standard deviation; Step Change is step change to observations ratio; Turn Point is turning point to observations ratio; Outlier is outliers larger than 3 standard deviations; CV is the coefficient of variation; ARCH = 1 is for an ARCH effect, = 0 otherwise; Extreme = 1 is for presence of extreme last observations, = 0 otherwise; Trend = 1 when basic trend is similar to recent trend, = 0 otherwise; Discont = 1 when there are discontinues in the series, = 0 otherwise; Obs is number of sample observations. ARCH is determined from residuals of the lowest AIC ARIMA model. Dummy = 1 when series is not finance-related, = 0 otherwise. Likelihood ratio for this model against a model with a constant is 0.057. Standard deviations are in parentheses. * is significant at 5 %.

Table 12 Monthly Data Series MNL Model Coefficient Estimates – RelMAE

Individual and Aggregate Selection

To determine if the individual model selection via the MNL model is better at selecting the better forecast model, the results of the individual selection using the MNL model are compared against forecasts of the aggregate selected model. Fildes (1989) suggests applying the aggregate model to forecast short leads achieves similar results to individually selected models.

We have compared the mean of the best performing aggregate model and the individual selected model to the quarterly data. The results give little support for individual selection suggesting the selection models are not sufficiently accurate to capitalize on the

Method	Correctly Predicted	Actual	Percent Correct
ARARMA	50	129	38.8
ARIMA	117	225	52.0
Holt	4	75	5.3
Holt-D	79	183	43.2
Holt-W	21	144	14.6
RT	4	88	4.5
SES	12	147	8.2
Total	287	991	30.0

Table 13 Monthly Data Series Prediction – RelMAE

potential for improvement in individual selection (Fildes, 2001).

To determine if the forecasting performance is affected by data type we have also split the data into financial or non-financial sub-sets. The results show forecast accuracy is not affected by the type of data. However, a close inspection of the results indicates the improvements in forecasting the quarterly data with the individual selection via the MNL model are larger for nonfinancial series. This suggests the effectiveness of the individual selection (as measured by differences between the errors from the aggregate and individual selection methods) declines when the method is applied to financial data.

6 Conclusion

An MNL model relates best forecast method to data moments and selected data characteristics. The approach implicitly assumes a stable underlying relationship exists between data characteristics and better forecasting method. Encouragingly, the MNL model based on relative error measures such as the RelGRMSE and the RelMAE, in particular, is able to indicate the better forecasting model reasonably well for the Quarterly data. The poor result for the MNL for the monthly data may be due to the high random nature of the monthly data applied here. Not surprisingly, the results differ by error statistic and data periodicity with higher frequency data being more difficult to forecast. The study is exploratory in nature and another set of data characteristics may be more appropriate for particular series. The study also raises interesting questions about reasons for the prediction accuracy of RelGRMSE-based versus RelMAE-based models, despite the fact that the two measures are really quite similar. Finally, the MNL models appear unable to predict correctly methods that are best in relatively few instances.

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