A Comparison of the Standardized Prediction Error Criterion with other ARCH Model Selection Criteria

Evdokia Xekalaki* and Stavros Degiannakis

Department of Statistics, Athens University of Economics and Business, 76, Patission Street, 10434 Athens, Greece

Technical Report no 205, March 2004

Abstract

In this report, two important issues that arise in the evaluation of the standardized prediction error criterion (SPEC) model selection method are investigated in the context of a simulated options market. The first refers to the question of whether the performance of the SPEC algorithm is sensitive to the size of the sample used and the second to that of how the SPEC algorithm compares with other methods of model selection that measure the accuracy of the ARCH models to forecast the realized intra-day volatility.

Keywords and Phrases: ARCH models, Forecast Volatility, Model selection, Option Pricing, Predictability, Standardized Prediction Error Criterion

* Corresponding author. Tel.: +30-210-8203269; fax: +30-210-8238798.
E-mail address: exek@aueb.gr .

1. Introduction

Degiannakis and Xekalaki (2002) investigated the performance of the SPEC algorithm as an ARCH model selection method through the simulation of an options market. In section 2, the simulation study is repeated twice using S&P500 stock index daily returns form July 10th, 1987 to October 18th, 2002 (3853 trading days) using larger samples of 1000 and 2000 observations in order to investigate whether the evaluation results concerning the SPEC are affected by the size of the sample. It turns out that the performance of the SPEC method is qualitatively the same for all the sample sizes.

In the section 3, model selection criteria that measure the accuracy of the models to predict the realized volatility are constructed and the SPEC method is compared with those model selection methods. It turns out that traders who base their selection of a model on the SPEC algorithm achieve higher profits than the traders who use intra-day volatility based methods of model selection. Finally, in section 4 a brief discussion of the results is provided.

2. Investigating the performance of the SPEC algorithm using larger sample sizes for the estimation of the ARCH models

Following Degiannakis and Xekalaki's (2002) set-up, a simulated options market consisting of 104 traders is created. Each trader uses his/her own variance forecast obtained by the model of his/her choice to price a straddle on the S&P500 index for the next day. The variance forecast methods that are compared are: 85 selection strategies, one for each of 85 ARCH models, each amounting to the utilization of the forecasts of the same model at any point in time, the SPEC model selection algorithm for 16 different sample sizes, the average, the minimum and the maximum of all daily forecasts methods.

The ARCH model is presented in a regression form by letting ε_t be the innovation process in a linear regression:

$$y_t = c_0 + \sum_{i=1}^{\kappa}\left(c_i y_{t-i}\right) + z_t\sigma_t$$

$$z_t \overset{i.i.d.}{\sim} N(0,1).$$

The conditional variance is regarded as a GARCH(p,q) model

$$\sigma_t^2 = a_0 + \sum_{i=1}^{q}\left(a_i\varepsilon_{t-i}^2\right) + \sum_{j=1}^{p}\left(b_j\sigma_{t-j}^2\right),$$

an EGARCH(p,q) model

$$\ln\left(\sigma_t^2\right)=a_0+\sum_{i=1}^{q}\left(a_i\left(\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|-E\left|\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right|\right)+\gamma_i\left(\frac{\varepsilon_{t-i}}{\sigma_{t-i}}\right)\right)+\sum_{j=1}^{p}\left(b_j\ln\left(\sigma_{t-j}^2\right)\right),$$

and a TARCH(p,q)model

$$\sigma_t^2=a_0+\sum_{i=1}^{q}\left(a_i\varepsilon_{t-i}^2\right)+\gamma\varepsilon_{t-1}^2 D\left(\varepsilon_{t-1}<0\right)+\sum_{j=1}^{p}\left(b_j\sigma_{t-j}^2\right),$$

where $D(\varepsilon_t<0)=1$ if $\varepsilon_t<0$, and $D(\varepsilon_t<0)=0$ otherwise. Thus, the AR(κ)GARCH(p,q), AR(κ)EGARCH(p,q) and AR(κ)TARCH(p,q) models are applied, for $\kappa=0,\ldots,4$, $p=0,1,2$ and $q=1,2$, yielding a total of 85 cases[1].

However, as has been noted in the literature, although the use of the entire set of available data is common practice in forecasting volatility, at least for some cases, a restricted sample size could generate more accurate one-step-ahead forecasts, since it incorporates changes in trading behaviour more efficiently. For example, Hoppe (1998) examined the issue of the sample size, in the context of value-at-risk, and argued that a smaller sample could lead to more accurate estimates than a larger one. Frey and Michaud (1997) supported the use of small sample sizes in order to capture the structural changes over time due to changes in trading behaviour. Degiannakis et al. (2003) note similar findings.

In order to investigate whether the use of a rolling sample size of 500 observations induces a bias on the results of the simulation, we re-run the simulation study with larger datasets. We used rolling samples of 1000 and 2000 observations and we found out that the results of Degiannakis and Xekalaki (2002) are not appreciably different when using sample sizes of 500, 1000 or 2000 observations.

Tables 1 to 3 present the profits per competitor per straddle and the corresponding t-ratios when we use rolling samples of 500, 1000 and 2000 observations, respectively (Table 1 is reprinted from Degiannakis and Xekalaki (2002)). There is no qualitative difference among the used sample sizes. The SPEC algorithm performs best for low values of T, (T=5, 10), in the new simulation studies, which is in complete agreement with the originally obtained results on the basis of a 500-observation rolling sample. The MINIMUM forecast takes the last positions and the MAXIMUM forecast achieves negative and statistically significant returns, an indication that neither a downward nor an upward forecast bias, that could affect profits significantly, is present.

It is interesting to note that the EGARCH(1,2), TARCH(1,2) and the TARCH(2,2) model selection algorithms perform distinctly better that the remaining ARCH models. The more flexible models, which account for the leverage effect and have a higher order of p,q,

[1] Numerical maximization of the log-likelihood function, for the E-GARCH(2,2) model, frequently failed to converge, for all the used sample sizes. So the five E-GARCH(2,2) models were excluded.

outperform the parsimonious models (i.e. GARCH(0,1), TARCH(0,1) and EGARCH(0,1)). Giot and Laurent (2003), Hansen and Lunde (2001) and Vilasuso (2002), among others, have found that more flexible models beat the forecasting ability of the parsimonious ones. Of course, as the number of candidate models increases, the probability of finding models with superior predictive ability will increase as well. Note that in our simulation study, we include 3 conditional variance specifications and Degiannakis and Xekalaki (2004) have presented 31 conditional variance specifications in the context of the ARCH framework. However, the investigation of the SPEC algorithm performance with a set of more flexible ARCH models, which account for recent developments in the area of asset returns volatility, is suggested for further research.

As there is no qualitative difference between the use of sample sizes of 1000 and 2000 observations, we present the results based on the sample size of 1000. Dropping out the trader with the least profitable method at a time, the cumulative profits of the participants in the simulated market are calculated. The SPEC(5) model selection algorithm achieves the highest returns in all the cases, thus indicating that the forecasting ability is not sensitive to the models that are used. As concerns the sample size of 1000 observations, Table 4 presents the transitivity of the profitability of competitors, who employ the SPEC model selection algorithm and the AVERAGE method. Table 5 shows the ranking and cumulative profits of the competitors trading straddles with exercise prices equal to e^{5rf_t}, e^{rf_t} and e^{-3rf_t}. The rank of the traders does not change significantly. So, the cumulative profits in the simulated market are not sensitive to the exercise price is used. The results of Table 4 and 5 are almost identical to those presented in Degiannakis and Xekalaki (2002) for a sample size of 500 observations.

3. Comparing Different Methods of Model Selection on Simulated Options

The selection of the appropriate model is one of the most challenging areas in statistical modeling. Usually, a researcher has to choose among a set of candidate models. Methods of model selection examine the ability of the models either to describe or to forecast the variable under investigation. The Akaike information criterion (Akaike (1973)) and the Schwarz Bayesian criterion (Schwarz (1978)) are model selection methods that are based on the maximized value of the log-likelihood function and evaluate the ability of the models to describe the data. In the case we are interesting in using a model for forecasting, the evaluation of the models should be based on their ability to produce valuable forecasts. Loss functions, which measure either the distance between actual and predicted values or the benefit from the use of these forecasts, are used to evaluate the forecasting ability of the models. Poon and Granger (2003) reviewed a detailed record of volatility forecasting loss functions and relative references.

In the sequel, the performance of the SPEC model selection algorithm is compared with other methods of selection that measure the ability of the models to forecast volatility. Denoting the realized at time $t+1$ by s_{t+1}^2, the following loss functions are considered:

1. Mean Square Error of Variance (MSEV):
$$T^{-1}\sum_{t=1}^{T}\left(\hat{\sigma}_{t+1|t}^2 - s_{t+1}^2\right)^2$$
2. Mean Absolute Error of Variance (MAEV):
$$T^{-1}\sum_{t=1}^{T}\left|\hat{\sigma}_{t+1|t}^2 - s_{t+1}^2\right|$$
3. Mean Square Error of Deviation (MSED):
$$T^{-1}\sum_{t=1}^{T}\left(\hat{\sigma}_{t+1|t} - s_{t+1}\right)^2$$
4. Mean Absolute Error of Deviation (MAED):
$$T^{-1}\sum_{t=1}^{T}\left|\hat{\sigma}_{t+1|t} - s_{t+1}\right|$$
5. Heteroscedasticity Adjusted Mean Squared Error of Variance (HAMSEV):
$$T^{-1}\sum_{t=1}^{T}\left(1 - s_{t+1}^2 / \hat{\sigma}_{t+1|t}^2\right)^2$$
6. Heteroscedasticity Adjusted Mean Absolute Error of Variance (HAMAEV):
$$T^{-1}\sum_{t=1}^{T}\left|1 - s_{t+1}^2 / \hat{\sigma}_{t+1|t}^2\right|$$
7. Heteroscedasticity Adjusted Mean Squared Error of Deviation (HAMSED):
$$T^{-1}\sum_{t=1}^{T}\left(1 - s_{t+1} / \hat{\sigma}_{t+1|t}\right)^2$$
8. Heteroscedasticity Adjusted Mean Absolute Error of Deviation (HAMAED):
$$T^{-1}\sum_{t=1}^{T}\left|1 - s_{t+1} / \hat{\sigma}_{t+1|t}\right|$$
9. Mean Logarithmic Error of Variance (MLEV):
$$T^{-1}\sum_{t=1}^{T}\ln\left(s_{t+1}^2 / \hat{\sigma}_{t+1|t}^2\right)^2$$
10. Gaussian Maximum Likelihood Error of Variance (GMLEV):
$$T^{-1}\sum_{t=1}^{T}\left(\ln\left(\hat{\sigma}_{t+1|t}^2\right) + \left(\frac{s_{t+1}^2}{\hat{\sigma}_{t+1|t}^2}\right)\right)$$
11. Gaussian Maximum Likelihood Error of Deviation (GMLED):
$$T^{-1}\sum_{t=1}^{T}\left(\ln\left(\hat{\sigma}_{t+1|t}\right) + \left(\frac{s_{t+1}}{\hat{\sigma}_{t+1|t}}\right)\right),$$

where T is the number of the one-step-ahead volatility forecasts. The first four loss functions have been widely used in applied studies. The heteroscedasticity adjusted functions were introduced by Andersen et al. (1999) and Bollerslev and Ghysels (1996), while mean logarithmic error function was utilized by Pagan and Schwert (1990). The GMLE function, which was presented in Bollerslev et al. (1994), measure the forecast error according to the likelihood function that is used in estimating the models.

As the actual volatility is unobservable, the common way to determine the daily realized volatility is the squared daily returns, which is an unbiased but noisy volatility estimator. Andersen and Bollerslev (1998) introduced the use of the sum squared finely sampled high frequency data as an alternative volatility measure. For a detailed description of the realized intra-day volatility, the interested reader is referred to Andersen et al. (2003) and Andersen et al. (2004). Based on Andersen et al. (1999), Andersen et al. (2001) and Kayahan et al. (2002), we compute the realized intra-day volatility of day t as:

$$s_t^2 = \sum_{j=1}^{m-1} \left(\ln\left(P_{(j+1/m),t}\right) - \ln\left(P_{(j/m),t}\right) \right)^2 ,$$

where $P_{(m),t}$ denotes five-minute linearly interpolated prices of S&P500 at day t with m observations per day. The intra-day quotation data are available from April 28th 1997 to October 18th 2002 and were provided by Olsen and Associates.

Each loss function is computed for $T = 10(10)80$. In order to compare the SPEC algorithm with the 11 loss functions, a simulated options market is created. Each agent selects the ARCH model with the lowest value of its the loss function in order to forecast next day's variance. The simulated market is consisting of 99 traders: the 12 model selection algorithms for 8 different sample sizes (including the SPEC algorithm), the average, the minimum and the maximum of all daily forecasts methods.

Table 6 presents for each model selection method the annualized daily profits. Traders who are based on the SPEC algorithm achieve the highest returns, despite the use of the realized intra-day volatility by the loss functions. Moreover, the SPEC method appears more suitable in predicting volatility for pricing contingent claims, as it is the only model selection method that produces returns higher that the AVERAGE algorithm does. An interesting point is that almost all the algorithms achieve their highest returns for $T = 10$.

4. Discussion

Degiannakis and Xekalaki (2002) examined the usage of the SPEC model selection algorithm based on Engle et al.'s (1993) technique to compare a group of variance forecast methods using a simulated options market. The present study extended the examined period from July 9th, 1987 to October 18th, 2002 and estimated the ARCH models using larger sample sizes of 1000 and 2000 observations. The results show that the performance of the SPEC algorithm is not affected by the size of the sample used.

The ability of the SPEC model selection algorithm was also compared with loss functions that measure the ability of the models to forecast volatility. Even though, the loss functions used the realized intra-day volatility, the SPEC algorithm, for $T = 10$, achieved the highest profits. The evidence provided by the results indicates that the increase in profits cannot be attributed to chance, but it can rather be considered as reflective of improved volatility prediction. Thus, the SPEC selection method appears to be a useful tool in guiding one's choice of the appropriate model for estimating future volatility.

References

Akaike, H., 1973. Information Theory and the Extension of the Maximum Likelihood Principle. Proceeding of the Second International Symposium on Information Theory. Budapest, 267-281.

Andersen, T.G. and Bollerslev, T., 1998. Answering the Skeptics: Yes, Standard Volatility Models Do Provide Accurate Forecasts. International Economic Review, 39, 885-905.

Andersen, T.G., Bollerslev, T. and Lange, S. 1999. Forecasting Financial Market Volatility: Sample Frequency vis-à-vis Forecast Horizon. Journal of Empirical Finance, 6, 457-477.

Andersen, T.G., Bollerslev, T., Diebold, F.X. and Ebens H., 2001. The Distribution of Stock Return Volatility. Journal of Financial Economics, 61, 43-76.

Andersen, T.G., Bollerslev, T., Diebold, F.X. and Labys, P., 2003. Modeling and Forecasting Realized Volatility. Econometrica, 71, 529-626.

Andersen, T.G., Bollerslev, T. and Diebold, F.X., 2004. Parametric and Nonparametric Volatility Measurement. Handbook of Financial Econometrics, (eds.) Yacine Aït-Sahalia and Lars Peter Hansen, Amsterdam, North Holland, forthcoming.

Bollerslev, T. and Ghysels, E., 1996. Periodic Autoregressive Conditional Heteroskedasticity, Journal of Business and Economic Statistics, 14, 139-157.

Bollerslev, T., Engle, R.F. and Nelson, D., 1994. ARCH Models. In R.F. Engle and D.L. McFadden (Ed.), Handbook of Econometrics, Ch.49, IV Elsevier.

Degiannakis, S. and Xekalaki, E., 2002. Using the Prediction Error Criterion as a Selection Method in Forecasting Option Prices: A Simulation Approach. Technical Report no 191, Athens University of Economics and Business, Department of Statistics. (http://stat-athens.aueb.gr/~exek/papers/Xekalaki-TechnRep191(2002)ft.pdf)

Degiannakis, S. and Xekalaki, E., 2004. Autoregressive Conditional Heteroscedasticity Models: A Review. Quality Technology and Quantitative Management, 1, 2, (To appear).

Degiannakis, S., Angelidis, T. and Benos A., 2003. The Use of GARCH Models in VaR Estimation. Technical Report no 204, Athens University of Economics and Business, Department of Statistics. (http://stat-athens.aueb.gr/~sdegia/)

Engle, R.F., Hong, C.H., Kane, A. and Noh, J., 1993. Arbitrage Valuation of Variance Forecasts with Simulated Options. Advances in Futures and Options Research, 6, 393-415.

Frey, R. and Michaud, P., 1997. The Effect of GARCH-type Volatilities on Prices and Payoff-Distributions of Derivative Assets - a Simulation Study, ETH Zurich, Working Paper.

Giot, P. and Laurent, S., 2003. Value-at-Risk for Long and Short Trading Positions. Journal of Applied Econometrics, 18, 641-664.

Hansen, P.R. and Lunde, A., 2001. A Forecast Comparison of Volatility Models: Does Anything Beat a GARCH(1,1)? Brown University, Department of Economics, Working Paper.

Hoppe, R., 1998. VAR and the unreal world, Risk, 11, 45-50.

Kayahan B., Saltoglu, T. and Stengos, T., 2002. Intra-Day Features of Realized Volatility: Evidence from an Emerging Market. International Journal of Business and Economics, 1(1), 17-24.

Pagan, A.R. and Schwert, G.W., 1990. Alternative Models for Conditional Stock Volatility. Journal of Econometrics, 45, 267-290.

Poon, S.H. and Granger, C.W.J., 2003. Forecasting Volatility in Financial Markets: A Review, Journal of Economic Literature, XLI, 478-539.

Schwarz, G., 1978. Estimating the Dimension of a Model. Annals of Statistics, 6, 461-464.

Vilasuso, J., 2002. Forecasting Exchange Rate Volatility. Economics Letters, 76, 59-64.

Table 1

The annualised daily profits per competitor per straddle for trades that are at the average of the bid/ask spread, using rolling samples of 500 observations.

Rank	Algorithm	Profit	T-Ratio	Rank	Algorithm	Profit	T-Ratio	Rank	Algorithm	Profit	T-Ratio
1	SPEC(T=5)	21.79%	5.4	36	AR(3)TARCH(2,1)	5.74%	1.6	71	AR(0)GARCH(0,2)	-8.80%	-2.5
2	SPEC(T=30)	19.92%	6.3	37	AR(2)EGARCH(1,2)	5.72%	1.8	72	AR(4)TARCH(0,2)	-8.97%	-2.5
3	SPEC(T=10)	19.59%	5.3	38	AR(2)EGARCH(2,1)	5.60%	2.0	73	AR(1)EGARCH(0,2)	-9.02%	-2.9
4	SPEC(T=25)	19.03%	6.0	39	AR(1)EGARCH(1,2)	4.48%	1.4	74	AR(2)TARCH(0,2)	-9.04%	-2.5
5	SPEC(T=35)	18.55%	6.4	40	AR(0)TARCH(2,1)	4.46%	1.2	75	AR(1)TARCH(0,2)	-9.06%	-2.5
6	SPEC(T=20)	18.41%	5.5	41	AR(3)TARCH(0,1)	4.06%	1.2	76	AR(3)GARCH(2,1)	-9.14%	-2.8
7	SPEC(T=15)	18.22%	5.3	42	AR(2)TARCH(0,1)	4.01%	1.3	77	AR(2)GARCH(2,1)	-9.22%	-3.0
8	AR(4)TARCH(1,2)	15.87%	6.1	43	AR(3)EGARCH(1,2)	3.85%	1.2	78	AR(4)GARCH(1,1)	-9.26%	-2.9
9	SPEC(T=45)	15.73%	5.7	44	AR(4)EGARCH(1,2)	3.73%	1.1	79	AR(1)GARCH(1,1)	-9.26%	-3.1
10	AR(0)TARCH(1,2)	15.06%	5.9	45	AR(4)TARCH(0,1)	3.25%	1.0	80	AR(3)TARCH(0,2)	-9.29%	-2.5
11	AR(2)TARCH(1,2)	14.94%	5.8	46	AR(2)EGARCH(1,1)	2.61%	0.9	81	AR(4)EGARCH(0,2)	-9.32%	-2.8
12	AR(1)TARCH(1,2)	14.85%	5.7	47	AR(3)EGARCH(2,1)	2.30%	0.8	82	AR(3)EGARCH(0,2)	-9.37%	-2.9
13	AR(3)TARCH(1,2)	14.81%	5.8	48	AR(4)EGARCH(2,1)	1.76%	0.6	83	AR(2)EGARCH(0,2)	-9.38%	-3.0
14	SPEC(T=40)	14.47%	5.2	49	AR(1)EGARCH(2,1)	1.72%	0.6	84	AR(1)GARCH(2,1)	-9.60%	-3.0
15	SPEC(T=60)	13.99%	5.0	50	AR(1)EGARCH(1,1)	1.60%	0.5	85	AR(4)GARCH(1,2)	-9.97%	-3.0
16	AVERAGE	13.65%	12.3	51	AR(4)EGARCH(1,1)	1.25%	0.4	86	AR(3)GARCH(1,2)	-10.35%	-3.1
17	SPEC(T=80)	13.60%	4.5	52	AR(3)EGARCH(1,1)	1.07%	0.4	87	AR(1)GARCH(1,2)	-10.52%	-3.3
18	SPEC(T=50)	13.59%	5.0	53	AR(4)TARCH(1,1)	-1.56%	-0.4	88	AR(1)GARCH(0,2)	-11.07%	-3.2
19	SPEC(T=55)	13.22%	4.7	54	AR(3)TARCH(1,1)	-1.68%	-0.4	89	AR(2)GARCH(1,2)	-11.19%	-3.5
20	SPEC(T=70)	13.15%	4.7	55	AR(1)TARCH(1,1)	-1.79%	-0.4	90	AR(0)GARCH(0,1)	-11.39%	-3.2
21	SPEC(T=65)	13.13%	4.7	56	AR(0)TARCH(1,1)	-1.81%	-0.4	91	AR(2)GARCH(0,2)	-11.51%	-3.3
22	AR(1)TARCH(2,2)	12.82%	4.7	57	AR(2)TARCH(1,1)	-2.41%	-0.6	92	AR(1)GARCH(0,1)	-11.62%	-3.1
23	SPEC(T=75)	12.62%	4.3	58	AR(0)GARCH(1,1)	-2.87%	-1.2	93	AR(2)GARCH(0,1)	-12.20%	-3.3
24	AR(2)TARCH(2,2)	10.19%	3.8	59	AR(0)GARCH(2,2)	-3.58%	-1.2	94	AR(3)GARCH(0,2)	-12.37%	-3.5
25	AR(3)TARCH(2,2)	9.69%	3.6	60	AR(0)GARCH(2,1)	-3.83%	-1.5	95	AR(3)GARCH(0,1)	-12.56%	-3.3
26	AR(0)TARCH(2,2)	9.43%	3.2	61	AR(0)GARCH(1,2)	-4.12%	-1.4	96	AR(4)GARCH(0,2)	-12.68%	-3.4
27	AR(4)TARCH(2,2)	9.35%	3.4	62	AR(0)EGARCH(0,2)	-6.81%	-2.1	97	AR(4)GARCH(0,1)	-12.92%	-3.4
28	AR(2)TARCH(2,1)	8.56%	2.4	63	AR(1)GARCH(2,2)	-7.36%	-2.3	98	AR(1)EGARCH(0,1)	-16.17%	-4.4
29	AR(0)TARCH(0,1)	8.35%	2.9	64	AR(3)GARCH(1,1)	-7.62%	-2.5	99	AR(2)EGARCH(0,1)	-16.94%	-4.5
30	AR(1)TARCH(2,1)	7.84%	2.3	65	AR(4)GARCH(2,2)	-7.69%	-2.3	100	AR(0)EGARCH(0,1)	-17.14%	-4.6
31	AR(4)TARCH(2,1)	7.03%	1.9	66	AR(0)TARCH(0,2)	-7.70%	-2.2	101	AR(3)EGARCH(0,1)	-17.52%	-4.7
32	AR(0)EGARCH(1,2)	6.87%	2.3	67	AR(4)GARCH(2,1)	-7.81%	-2.4	102	AR(4)EGARCH(0,1)	-17.92%	-4.7
33	AR(0)EGARCH(2,1)	6.42%	2.4	68	AR(2)GARCH(2,2)	-7.88%	-2.4	103	MAXIMUM	-18.60%	-3.3
34	AR(0)EGARCH(1,1)	6.07%	2.2	69	AR(3)GARCH(2,2)	-8.13%	-2.4	104	MINIMUM	-33.35%	-5.9
35	AR(1)TARCH(0,1)	5.82%	1.8	70	AR(2)GARCH(1,1)	-8.16%	-2.7				

Table 2

The annualised daily profits per competitor per straddle for trades that are at the average of the bid/ask spread, using rolling samples of 1000 observations.

Rank	Algorithm	Profit	T-Ratio	Rank	Algorithm	Profit	T-Ratio	Rank	Algorithm	Profit	T-Ratio
1	SPEC(T=5)	22.34%	6.76	36	AR(2)EGARCH(2,1)	8.71%	4.12	71	AR(2)GARCH(1,2)	-4.69%	-1.77
2	SPEC(T=10)	20.09%	6.64	37	AR(0)EGARCH(2,1)	8.64%	3.98	72	AR(4)GARCH(1,2)	-5.04%	-1.85
3	SPEC(T=15)	17.94%	6.53	38	AR(4)EGARCH(1,1)	8.44%	4.36	73	AR(0)EGARCH(0,2)	-6.45%	-1.89
4	SPEC(T=25)	16.58%	6.70	39	AR(4)TARCH(1,2)	8.11%	3.36	74	AR(1)EGARCH(0,2)	-6.90%	-2.02
5	SPEC(T=20)	16.56%	6.49	40	AR(0)TARCH(1,1)	7.80%	3.58	75	AR(2)EGARCH(0,2)	-7.20%	-2.11
6	AR(0)EGARCH(1,2)	14.44%	5.49	41	AR(1)EGARCH(2,1)	7.62%	3.69	76	AR(3)EGARCH(0,2)	-7.60%	-2.24
7	SPEC(T=50)	14.42%	6.35	42	AR(3)EGARCH(2,1)	7.53%	3.71	77	AR(4)EGARCH(0,2)	-7.83%	-2.31
8	SPEC(T=40)	14.29%	5.91	43	AR(0)TARCH(2,1)	7.26%	3.33	78	MAXIMUM	-10.38%	-2.27
9	SPEC(T=30)	13.93%	5.78	44	AR(4)EGARCH(2,1)	6.87%	3.44	79	AR(0)TARCH(0,2)	-11.66%	-4.01
10	SPEC(T=45)	13.85%	5.73	45	AR(2)TARCH(1,1)	6.72%	3.01	80	AR(2)TARCH(0,2)	-12.18%	-4.19
11	SPEC(T=35)	13.80%	5.69	46	AR(1)TARCH(1,1)	6.50%	2.82	81	AR(3)TARCH(0,2)	-12.57%	-4.26
12	SPEC(T=80)	13.49%	5.75	47	AR(2)TARCH(2,1)	6.14%	2.87	82	AR(1)TARCH(0,2)	-12.69%	-4.35
13	SPEC(T=55)	13.10%	5.56	48	AR(1)TARCH(2,1)	6.02%	2.75	83	AR(4)TARCH(0,2)	-13.00%	-4.30
14	SPEC(T=70)	13.04%	5.48	49	AR(3)TARCH(2,1)	5.91%	2.82	84	AR(0)GARCH(0,2)	-13.35%	-4.48
15	SPEC(T=60)	12.84%	5.43	50	AR(3)TARCH(1,1)	5.61%	2.60	85	AR(1)GARCH(0,2)	-13.80%	-4.66
16	SPEC(T=65)	12.70%	5.39	51	AR(4)TARCH(1,1)	5.54%	2.56	86	AR(2)GARCH(0,2)	-13.84%	-4.66
17	AR(0)TARCH(2,2)	12.61%	5.65	52	AR(4)TARCH(2,1)	4.65%	2.25	87	AR(3)GARCH(0,2)	-14.29%	-4.72
18	AR(1)EGARCH(1,2)	12.54%	4.88	53	AR(0)GARCH(2,1)	-0.49%	-0.19	88	AR(4)GARCH(0,2)	-14.33%	-4.64
19	AR(2)EGARCH(1,2)	12.44%	4.96	54	AR(0)GARCH(1,2)	-0.66%	-0.27	89	AR(0)EGARCH(0,1)	-16.93%	-5.43
20	AR(3)EGARCH(1,2)	12.12%	4.88	55	AR(0)GARCH(2,2)	-0.68%	-0.27	90	AR(1)EGARCH(0,1)	-17.79%	-5.61
21	SPEC(T=75)	12.02%	5.11	56	AR(0)GARCH(1,1)	-1.50%	-0.59	91	AR(2)EGARCH(0,1)	-17.91%	-5.59
22	AR(4)EGARCH(1,2)	12.01%	4.82	57	AR(1)GARCH(2,1)	-1.59%	-0.60	92	AR(3)EGARCH(0,1)	-18.22%	-5.68
23	AR(0)EGARCH(1,1)	11.32%	5.41	58	AR(3)GARCH(2,2)	-1.89%	-0.71	93	AR(4)EGARCH(0,1)	-18.27%	-5.68
24	AR(1)TARCH(2,2)	11.04%	4.95	59	AR(1)GARCH(2,2)	-1.94%	-0.74	94	AR(0)GARCH(0,1)	-20.26%	-6.39
25	AR(0)TARCH(1,2)	10.88%	4.52	60	AR(2)GARCH(2,1)	-1.99%	-0.75	95	AR(1)GARCH(0,1)	-20.49%	-6.35
26	AR(2)TARCH(2,2)	10.74%	4.88	61	AR(3)GARCH(2,1)	-2.00%	-0.75	96	AR(2)GARCH(0,1)	-20.89%	-6.45
27	AR(2)EGARCH(1,1)	10.69%	5.31	62	AR(2)GARCH(2,2)	-2.62%	-1.00	97	AR(3)GARCH(0,1)	-21.10%	-6.45
28	AR(2)TARCH(1,2)	10.31%	4.17	63	AR(1)GARCH(1,2)	-2.70%	-1.03	98	AR(0)TARCH(0,1)	-21.29%	-6.84
29	AR(1)EGARCH(1,1)	10.24%	4.89	64	AR(4)GARCH(2,1)	-2.72%	-1.02	99	AR(4)GARCH(0,1)	-21.64%	-6.54
30	AR(3)TARCH(2,2)	10.05%	4.68	65	AR(1)GARCH(1,1)	-3.22%	-1.26	100	AR(1)TARCH(0,1)	-21.90%	-6.94
31	AR(4)TARCH(2,2)	9.41%	4.31	66	AR(3)GARCH(1,1)	-3.29%	-1.24	101	AR(2)TARCH(0,1)	-22.00%	-6.95
32	AVERAGE	9.28%	9.33	67	AR(2)GARCH(1,1)	-3.63%	-1.40	102	AR(3)TARCH(0,1)	-22.24%	-7.08
33	AR(3)EGARCH(1,1)	9.23%	4.72	68	AR(4)GARCH(1,1)	-3.64%	-1.37	103	AR(4)TARCH(0,1)	-22.25%	-7.02
34	AR(1)TARCH(1,2)	8.94%	3.53	69	AR(4)GARCH(2,2)	-3.65%	-1.37	104	MINIMUM	-37.99%	-8.20
35	AR(3)TARCH(1,2)	8.89%	3.77	70	AR(3)GARCH(1,2)	-4.28%	-1.62				

Table 3

The annualised daily profits per competitor per straddle for trades that are at the average of the bid/ask spread, using rolling samples of 2000 observations.

Rank	Algorithm	Profit	T-Ratio	Rank	Algorithm	Profit	T-Ratio	Rank	Algorithm	Profit	T-Ratio
1	SPEC(T=5)	19.08%	5.63	36	AR(4)EGARCH(2,1)	9.82%	5.27	71	AR(1)GARCH(2,1)	-5.20%	-2.16
2	SPEC(T=10)	17.29%	5.69	37	AR(0)EGARCH(2,1)	9.82%	5.12	72	AR(3)GARCH(2,1)	-5.22%	-2.18
3	SPEC(T=40)	16.52%	7.09	38	AR(3)EGARCH(2,1)	9.51%	5.14	73	MAXIMUM	-9.42%	-2.04
4	SPEC(T=55)	16.24%	7.10	39	AR(3)TARCH(2,2)	9.42%	4.25	74	AR(0)EGARCH(0,2)	-10.19%	-2.82
5	SPEC(T=50)	15.89%	7.04	40	AVERAGE	9.37%	8.13	75	AR(4)EGARCH(0,2)	-10.25%	-2.83
6	SPEC(T=25)	15.43%	6.26	41	AR(2)EGARCH(2,1)	8.98%	4.56	76	AR(3)EGARCH(0,2)	-10.29%	-2.86
7	SPEC(T=65)	15.41%	6.88	42	AR(0)TARCH(1,1)	8.93%	4.07	77	AR(2)EGARCH(0,2)	-10.58%	-2.95
8	SPEC(T=45)	15.38%	6.65	43	AR(0)TARCH(2,1)	8.88%	4.20	78	AR(1)EGARCH(0,2)	-10.63%	-2.95
9	SPEC(T=35)	15.26%	6.63	44	AR(1)EGARCH(2,1)	8.73%	4.30	79	AR(0)TARCH(0,2)	-11.50%	-3.70
10	SPEC(T=15)	15.19%	5.47	45	AR(1)TARCH(2,1)	7.60%	3.56	80	AR(0)GARCH(0,2)	-12.52%	-4.03
11	SPEC(T=20)	14.85%	5.73	46	AR(2)TARCH(1,1)	7.16%	3.30	81	AR(1)TARCH(0,2)	-13.32%	-4.30
12	SPEC(T=60)	14.82%	6.44	47	AR(1)TARCH(1,1)	7.02%	3.22	82	AR(4)TARCH(0,2)	-13.58%	-4.28
13	SPEC(T=70)	14.61%	6.37	48	AR(2)TARCH(2,1)	6.66%	3.19	83	AR(2)TARCH(0,2)	-13.60%	-4.35
14	SPEC(T=30)	14.51%	6.26	49	AR(4)TARCH(1,1)	6.53%	3.25	84	AR(3)TARCH(0,2)	-13.65%	-4.35
15	AR(0)EGARCH(1,2)	14.22%	5.43	50	AR(4)TARCH(2,1)	6.50%	3.16	85	AR(1)GARCH(0,2)	-14.02%	-4.49
16	AR(1)EGARCH(1,1)	13.57%	7.18	51	AR(3)TARCH(1,1)	5.60%	2.66	86	AR(4)GARCH(0,2)	-14.29%	-4.50
17	AR(2)EGARCH(1,1)	13.26%	7.09	52	AR(3)TARCH(2,1)	4.64%	2.25	87	AR(2)GARCH(0,2)	-14.50%	-4.60
18	AR(0)TARCH(1,2)	12.92%	5.02	53	AR(0)GARCH(1,2)	-0.12%	-0.05	88	AR(3)GARCH(0,2)	-14.50%	-4.58
19	AR(1)EGARCH(1,2)	12.85%	5.05	54	AR(0)GARCH(2,2)	-0.29%	-0.12	89	AR(0)EGARCH(0,1)	-16.91%	-5.10
20	AR(4)EGARCH(1,1)	12.74%	6.85	55	AR(1)GARCH(2,2)	-1.64%	-0.66	90	AR(1)EGARCH(0,1)	-17.02%	-5.08
21	AR(0)EGARCH(1,1)	12.67%	6.68	56	AR(1)GARCH(1,2)	-1.74%	-0.73	91	AR(2)EGARCH(0,1)	-17.42%	-5.20
22	AR(2)EGARCH(1,2)	12.50%	5.00	57	AR(4)GARCH(2,2)	-1.82%	-0.74	92	AR(3)EGARCH(0,1)	-17.50%	-5.20
23	AR(0)TARCH(2,2)	12.31%	5.47	58	AR(3)GARCH(2,2)	-2.96%	-1.17	93	AR(4)EGARCH(0,1)	-17.87%	-5.26
24	AR(4)EGARCH(1,2)	12.21%	4.81	59	AR(3)GARCH(1,2)	-3.11%	-1.23	94	AR(3)GARCH(0,1)	-20.29%	-6.19
25	AR(3)EGARCH(1,1)	12.16%	6.75	60	AR(0)GARCH(1,1)	-3.12%	-1.27	95	AR(2)GARCH(0,1)	-20.59%	-6.30
26	AR(1)TARCH(2,2)	12.01%	5.18	61	AR(2)GARCH(1,2)	-3.36%	-1.35	96	AR(0)GARCH(0,1)	-20.75%	-6.43
27	AR(2)TARCH(1,2)	12.00%	4.79	62	AR(2)GARCH(2,2)	-3.41%	-1.36	97	AR(1)GARCH(0,1)	-20.87%	-6.33
28	SPEC(T=75)	12.00%	5.49	63	AR(4)GARCH(1,2)	-3.70%	-1.47	98	AR(0)TARCH(0,1)	-21.15%	-6.22
29	AR(3)EGARCH(1,2)	11.15%	4.49	64	AR(3)GARCH(1,1)	-3.74%	-1.46	99	AR(4)GARCH(0,1)	-21.17%	-6.36
30	AR(1)TARCH(1,2)	10.99%	4.24	65	AR(0)GARCH(2,1)	-4.00%	-1.67	100	AR(1)TARCH(0,1)	-21.34%	-6.26
31	AR(3)TARCH(1,2)	10.49%	4.16	66	AR(1)GARCH(1,1)	-4.15%	-1.68	101	AR(2)TARCH(0,1)	-21.59%	-6.36
32	AR(2)TARCH(2,2)	10.22%	4.56	67	AR(4)GARCH(1,1)	-4.23%	-1.66	102	AR(3)TARCH(0,1)	-21.78%	-6.37
33	SPEC(T=80)	10.21%	4.62	68	AR(4)GARCH(2,1)	-4.34%	-1.72	103	AR(4)TARCH(0,1)	-22.14%	-6.39
34	AR(4)TARCH(1,2)	9.84%	3.84	69	AR(2)GARCH(2,1)	-4.77%	-1.98	104	MINIMUM	-43.47%	-9.24
35	AR(4)TARCH(2,2)	9.84%	4.54	70	AR(2)GARCH(1,1)	-5.08%	-2.03				

Table 4

Rank of the methods based on the SPEC model selection algorithm by dropping out the least profitable agent at a time. ARCH models were estimated using rolling samples of 1000 observations.

	Algorithm																
Ranks in Groups by Size	SPEC (T=5)	SPEC (T=10)	SPEC (T=15)	SPEC (T=20)	SPEC (T=25)	SPEC (T=30)	SPEC (T=35)	SPEC (T=40)	SPEC (T=45)	SPEC (T=50)	SPEC (T=55)	SPEC (T=60)	SPEC (T=65)	SPEC (T=70)	SPEC (T=75)	SPEC (T=80)	AVERAGE
104	1	2	3	5	4	9	11	8	10	6	12	15	17	14	22	13	31
103	1	2	3	5	4	9	10	8	11	6	12	15	17	14	22	13	32
102	1	2	3	5	4	9	10	7	11	6	12	15	17	14	21	13	32
101	1	2	3	5	4	9	10	7	11	6	12	15	17	14	21	13	32
100	1	2	3	5	4	9	10	7	11	6	12	14	17	15	21	13	32
95	1	2	3	5	4	9	10	6	11	7	12	14	17	15	21	13	35
90	1	2	3	5	4	9	10	7	11	8	12	14	17	16	21	13	36
85	1	2	3	4	5	9	10	7	11	8	12	15	18	16	21	13	37
80	1	2	3	4	5	9	10	7	11	8	12	15	18	16	22	14	40
75	1	2	3	4	5	8	10	7	11	9	13	15	18	16	23	14	41
70	1	2	3	5	4	8	10	7	11	9	13	14	17	16	22	15	41
65	1	2	3	5	4	8	9	7	11	10	13	14	18	16	23	15	42
60	1	2	3	5	4	8	9	7	11	10	13	14	17	16	23	15	43
55	1	2	3	5	4	8	9	7	11	10	13	14	15	16	24	17	43
50	1	2	3	5	4	7	9	8	12	10	14	13	15	17	24	18	43
45	1	2	3	5	4	8	9	7	11	10	13	14	15	17	24	18	42
40	1	2	3	5	4	8	9	7	11	10	12	13	15	16	21	17	39
35	1	2	3	5	4	8	9	7	11	10	12	13	15	17	22	19	
30	1	2	4	5	3	9	8	7	11	10	13	12	14	17	21	19	
25	1	2	4	5	3	9	7	8	10	11	13	12	15	18	22	19	
20	1	2	3	5	4	10	7	8	9	11	13	12	17	19		20	
15	1	2	3	5	4	9	7	8	10	12	13	11					
14	1	2	3	5	4	10	7	8	9	12	13	11					
13	1	2	3	5	4	10	7	9	8	12	13	11					
12	1	2	3	5	4	11	7	9	10	12		8					
11	1	2	3	5	4	11	7	9	10			8					
10	1	2	3	5	4		7	9	10			8					
9	1	2	3	5	4		8	7				9					
8	1	2	3	5	4		8	7									
7	1	2	3	5	4			7									
6	1	2	3	5	4												
5	1	2	3	5	4												
4	1	2	3		4												
3	1	2	3														
2	1	2															

Table 5

The rank and annualized daily profits of the competitors trading one-day straddles with different exercise prices. ARCH models were estimated using rolling samples of 1000 observations.

Forecasts	K=exp(5r)		K=exp(r)		K=exp(-3r)		Forecasts	K=exp(5r)		K=exp(r)		K=exp(-3r)		Forecasts	K=exp(5r)		K=exp(r)		K=exp(-3r)	
	Profit	Rank	Profit	Rank	Profit	Rank		Profit	Rank	Profit	Rank	Profit	Rank		Profit	Rank	Profit	Rank	Profit	Rank
SPEC(T=5)	21,60%	1	21,79%	1	21,66%	1	AR(1)GARCH(1,2)	-10,53%	87	-10,52%	87	-10,52%	87	AR(1)EGARCH(2,1)	1,78%	49	1,72%	49	1,78%	49
SPEC(T=10)	19,43%	3	19,59%	3	19,48%	3	AR(2)GARCH(1,2)	-11,24%	89	-11,19%	89	-11,23%	89	AR(2)EGARCH(2,1)	5,65%	38	5,60%	38	5,65%	38
SPEC(T=15)	18,09%	7	18,22%	7	18,12%	7	AR(3)GARCH(1,2)	-10,41%	86	-10,35%	86	-10,40%	86	AR(3)EGARCH(2,1)	2,34%	47	2,30%	47	2,34%	47
SPEC(T=20)	18,30%	6	18,41%	6	18,33%	6	AR(4)GARCH(1,2)	-10,03%	85	-9,97%	85	-10,02%	85	AR(4)EGARCH(2,1)	1,80%	48	1,76%	48	1,80%	48
SPEC(T=25)	18,93%	4	19,03%	4	18,95%	4	AR(0)GARCH(2,1)	-3,87%	60	-3,83%	60	-3,87%	60	AR(0)TARCH(0,1)	8,39%	29	8,35%	29	8,39%	29
SPEC(T=30)	19,83%	2	19,92%	2	19,85%	2	AR(1)GARCH(2,1)	-9,58%	84	-9,60%	84	-9,58%	84	AR(1)TARCH(0,1)	5,86%	35	5,82%	35	5,86%	35
SPEC(T=35)	18,47%	5	18,55%	5	18,48%	5	AR(2)GARCH(2,1)	-9,26%	79	-9,22%	77	-9,25%	77	AR(2)TARCH(0,1)	4,04%	42	4,01%	42	4,04%	42
SPEC(T=40)	14,40%	14	14,47%	14	14,42%	14	AR(3)GARCH(2,1)	-9,18%	76	-9,14%	76	-9,17%	76	AR(3)TARCH(0,1)	4,09%	41	4,06%	41	4,09%	41
SPEC(T=45)	15,66%	9	15,73%	9	15,67%	9	AR(4)GARCH(2,1)	-7,87%	67	-7,81%	67	-7,86%	67	AR(4)TARCH(0,1)	3,28%	45	3,25%	45	3,28%	45
SPEC(T=50)	13,52%	17	13,59%	18	13,54%	17	AR(0)GARCH(2,2)	-3,63%	59	-3,58%	59	-3,62%	59	AR(0)TARCH(0,2)	-7,66%	64	-7,70%	66	-7,68%	65
SPEC(T=55)	13,17%	19	13,22%	19	13,18%	19	AR(1)GARCH(2,2)	-7,36%	63	-7,36%	63	-7,35%	63	AR(1)TARCH(0,2)	-9,04%	75	-9,06%	75	-9,05%	75
SPEC(T=60)	13,93%	15	13,99%	15	13,94%	15	AR(2)GARCH(2,2)	-7,93%	68	-7,88%	68	-7,92%	68	AR(2)TARCH(0,2)	-9,01%	74	-9,04%	74	-9,02%	74
SPEC(T=65)	13,05%	21	13,13%	21	13,06%	21	AR(3)GARCH(2,2)	-8,18%	69	-8,13%	69	-8,17%	69	AR(3)TARCH(0,2)	-9,26%	78	-9,29%	80	-9,27%	78
SPEC(T=70)	13,08%	20	13,15%	20	13,09%	20	AR(4)GARCH(2,2)	-7,74%	66	-7,69%	65	-7,73%	66	AR(4)TARCH(0,2)	-8,94%	72	-8,97%	72	-8,95%	72
SPEC(T=75)	12,54%	23	12,62%	23	12,55%	23	AR(0)EGARCH(0,1)	-17,09%	100	-17,14%	100	-17,11%	100	AR(0)TARCH(1,1)	-1,73%	56	-1,81%	56	-1,75%	56
SPEC(T=80)	13,52%	18	13,60%	17	13,53%	18	AR(1)EGARCH(0,1)	-16,15%	98	-16,17%	98	-16,16%	98	AR(1)TARCH(1,1)	-1,71%	55	-1,79%	55	-1,73%	55
MINIMUM	-32,93%	104	-33,35%	104	-33,02%	104	AR(2)EGARCH(0,1)	-16,91%	99	-16,94%	99	-16,92%	99	AR(2)TARCH(1,1)	-2,33%	57	-2,41%	57	-2,35%	57
MAXIMUM	-18,96%	103	-18,60%	103	-18,83%	103	AR(3)EGARCH(0,1)	-17,48%	101	-17,52%	101	-17,49%	101	AR(3)TARCH(1,1)	-1,59%	54	-1,68%	54	-1,61%	54
AVERAGE	13,63%	16	13,65%	16	13,62%	16	AR(4)EGARCH(0,1)	-17,87%	102	-17,92%	102	-17,88%	102	AR(4)TARCH(1,1)	-1,47%	53	-1,56%	53	-1,49%	53
AR(0)GARCH(0,1)	-11,35%	90	-11,39%	90	-11,37%	90	AR(0)EGARCH(0,2)	-6,74%	62	-6,81%	62	-6,76%	62	AR(0)TARCH(1,2)	15,07%	10	15,06%	10	15,06%	10
AR(1)GARCH(0,1)	-11,60%	92	-11,62%	92	-11,61%	92	AR(1)EGARCH(0,2)	-8,97%	73	-9,02%	73	-8,99%	73	AR(1)TARCH(1,2)	14,87%	12	14,85%	12	14,86%	12
AR(2)GARCH(0,1)	-12,17%	93	-12,20%	93	-12,19%	93	AR(2)EGARCH(0,2)	-9,32%	83	-9,38%	83	-9,34%	83	AR(2)TARCH(1,2)	14,96%	11	14,94%	11	14,95%	11
AR(3)GARCH(0,1)	-12,52%	95	-12,56%	95	-12,54%	95	AR(3)EGARCH(0,2)	-9,31%	80	-9,37%	82	-9,33%	82	AR(3)TARCH(1,2)	14,83%	13	14,81%	13	14,83%	13
AR(4)GARCH(0,1)	-12,89%	97	-12,92%	97	-12,90%	97	AR(4)EGARCH(0,2)	-9,25%	77	-9,32%	81	-9,27%	79	AR(4)TARCH(1,2)	15,90%	8	15,87%	8	15,89%	8
AR(0)GARCH(0,2)	-8,73%	71	-8,80%	71	-8,75%	71	AR(0)EGARCH(1,1)	6,11%	34	6,07%	34	6,11%	34	AR(0)TARCH(2,1)	4,52%	39	4,46%	40	4,51%	39
AR(1)GARCH(0,2)	-11,03%	88	-11,07%	88	-11,04%	88	AR(1)EGARCH(1,1)	1,60%	50	1,60%	50	1,61%	50	AR(1)TARCH(2,1)	7,89%	30	7,84%	30	7,88%	30
AR(2)GARCH(0,2)	-11,46%	91	-11,51%	91	-11,47%	91	AR(2)EGARCH(1,1)	2,61%	46	2,61%	46	2,61%	46	AR(2)TARCH(2,1)	8,60%	28	8,56%	28	8,59%	28
AR(3)GARCH(0,2)	-12,30%	94	-12,37%	94	-12,32%	94	AR(3)EGARCH(1,1)	1,10%	52	1,07%	52	1,10%	52	AR(3)TARCH(2,1)	5,79%	36	5,74%	36	5,78%	36
AR(4)GARCH(0,2)	-12,61%	96	-12,68%	96	-12,63%	96	AR(4)EGARCH(1,1)	1,30%	51	1,25%	51	1,30%	51	AR(4)TARCH(2,1)	7,08%	31	7,03%	31	7,07%	31
AR(0)GARCH(1,1)	-2,90%	58	-2,87%	58	-2,90%	58	AR(0)EGARCH(1,2)	6,91%	32	6,87%	32	6,91%	32	AR(0)TARCH(2,2)	9,48%	26	9,43%	26	9,47%	26
AR(1)GARCH(1,1)	-9,32%	81	-9,26%	79	-9,31%	81	AR(1)EGARCH(1,2)	4,45%	40	4,48%	39	4,46%	40	AR(1)TARCH(2,2)	12,84%	22	12,82%	22	12,84%	22
AR(2)GARCH(1,1)	-8,23%	70	-8,16%	70	-8,21%	70	AR(2)EGARCH(1,2)	5,73%	37	5,72%	37	5,74%	37	AR(2)TARCH(2,2)	10,21%	24	10,19%	24	10,21%	24
AR(3)GARCH(1,1)	-7,68%	65	-7,62%	64	-7,67%	64	AR(3)EGARCH(1,2)	3,89%	43	3,85%	43	3,89%	43	AR(3)TARCH(2,2)	9,72%	25	9,69%	25	9,71%	25
AR(4)GARCH(1,1)	-9,32%	82	-9,26%	78	-9,31%	80	AR(4)EGARCH(1,2)	3,77%	44	3,73%	44	3,77%	44	AR(4)TARCH(2,2)	9,38%	27	9,35%	27	9,38%	27
AR(0)GARCH(1,2)	-4,16%	61	-4,12%	61	-4,15%	61	AR(0)EGARCH(2,1)	6,46%	33	6,42%	33	6,46%	33							

Table 6

The annualized daily profits per competitor per straddle for trades that are at the average of the bid/ask spread. ARCH models were estimated using rolling samples of 1000 observations.

Rank	Model Selection Algorithm	Profit	T-Ratio	Rank	Model Selection Algorithm	Profit	T-Ratio	Rank	Model Selection Algorithm	Profit	T-Ratio
1	SPEC(T=10)	16.42%	3.51	34	MAEV(T=10)	-7.72%	-1.82	67	GMLEV(T=60)	-10.97%	-2.88
2	SPEC(T=20)	13.73%	3.09	35	HAMSED(T=20)	-7.79%	-1.96	68	GMLEV(T=30)	-11.02%	-2.95
3	SPEC(T=50)	13.59%	3.17	36	MSEV(T=70)	-8.06%	-2.17	69	MAED(T=80)	-11.07%	-2.90
4	AVERAGE	13.30%	4.67	37	MSEV(T=60)	-8.08%	-2.19	70	GMLEV(T=50)	-11.08%	-2.91
5	SPEC(T=30)	11.87%	2.74	38	GMLEV(T=20)	-8.35%	-2.06	71	HAMAED(T=40)	-11.20%	-2.93
6	SPEC(T=40)	11.64%	2.68	39	HAMAED(T=20)	-8.38%	-2.10	72	GMLEV(T=70)	-11.25%	-2.96
7	SPEC(T=60)	11.50%	2.65	40	MSEV(T=50)	-8.46%	-2.19	73	MSED(T=80)	-11.57%	-3.09
8	SPEC(T=70)	10.63%	2.48	41	MSEV(T=80)	-8.58%	-2.35	74	GMLED(T=70)	-11.75%	-3.02
9	SPEC(T=80)	8.62%	2.03	42	GMLED(T=50)	-8.60%	-2.34	75	MLEV(T=70)	-11.80%	-3.04
10	HAMSEV(T=10)	0.87%	0.21	43	HAMAEV(T=40)	-8.70%	-2.40	76	HAMAED(T=80)	-11.83%	-3.05
11	HAMAEV(T=10)	0.53%	0.13	44	HAMSED(T=40)	-8.94%	-2.41	77	GMLED(T=60)	-12.11%	-3.13
12	HAMSEV(T=20)	0.38%	0.09	45	HAMSED(T=60)	-9.30%	-2.54	78	MSED(T=60)	-12.42%	-3.27
13	HAMSEV(T=30)	0.04%	0.01	46	GMLED(T=20)	-9.61%	-2.41	79	HAMAED(T=50)	-12.44%	-3.29
14	HAMSED(T=10)	-0.29%	-0.07	47	MSED(T=70)	-9.90%	-2.58	80	MSED(T=30)	-12.45%	-3.12
15	HAMSEV(T=60)	-0.96%	-0.26	48	MSEV(T=20)	-9.92%	-2.40	81	MAEV(T=50)	-12.46%	-3.21
16	HAMSEV(T=80)	-1.05%	-0.28	49	HAMAEV(T=70)	-9.95%	-2.70	82	MLEV(T=30)	-12.65%	-3.22
17	MAX	-1.18%	-0.21	50	HAMAEV(T=50)	-10.04%	-2.81	83	MAED(T=50)	-12.68%	-3.24
18	HAMSEV(T=70)	-1.22%	-0.34	51	GMLED(T=30)	-10.11%	-2.66	84	HAMAED(T=70)	-12.87%	-3.23
19	GMLEV(T=10)	-1.66%	-0.40	52	HAMAEV(T=60)	-10.14%	-2.79	85	MAED(T=70)	-13.39%	-3.44
20	GMLED(T=10)	-1.93%	-0.47	53	MLEV(T=60)	-10.26%	-2.70	86	MSEV(T=30)	-13.44%	-3.34
21	HAMSEV(T=50)	-2.95%	-0.78	54	MLEV(T=20)	-10.32%	-2.58	87	MAEV(T=60)	-13.46%	-3.45
22	MLEV(T=10)	-3.20%	-0.77	55	HAMSED(T=30)	-10.38%	-2.72	88	HAMAED(T=60)	-13.70%	-3.44
23	HAMSEV(T=40)	-3.33%	-0.87	56	GMLEV(T=80)	-10.46%	-2.79	89	MAEV(T=20)	-13.74%	-3.30
24	HAMAED(T=10)	-3.81%	-0.94	57	MLEV(T=50)	-10.46%	-2.79	90	MAED(T=20)	-14.23%	-3.46
25	MSED(T=10)	-4.01%	-0.95	58	GMLED(T=40)	-10.51%	-2.76	91	MAEV(T=70)	-14.25%	-3.60
26	MSEV(T=10)	-4.28%	-1.01	59	HAMAEV(T=30)	-10.54%	-2.83	92	MAED(T=40)	-14.28%	-3.62
27	MAED(T=10)	-5.19%	-1.23	60	MLEV(T=40)	-10.55%	-2.82	93	MAEV(T=30)	-14.30%	-3.55
28	GMLEV(T=40)	-5.84%	-1.57	61	GMLED(T=80)	-10.61%	-2.76	94	MAEV(T=80)	-14.33%	-3.71
29	HAMAEV(T=80)	-6.44%	-1.77	62	MSED(T=20)	-10.67%	-2.64	95	MAED(T=30)	-14.53%	-3.60
30	HAMSED(T=80)	-6.66%	-1.80	63	MLEV(T=80)	-10.72%	-2.86	96	MAED(T=60)	-14.60%	-3.82
31	HAMSED(T=70)	-7.18%	-1.91	64	MSED(T=40)	-10.73%	-2.79	97	MAEV(T=40)	-16.09%	-4.06
32	HAMAEV(T=20)	-7.52%	-1.89	65	MSED(T=50)	-10.78%	-2.89	98	HAMAED(T=30)	-16.14%	-4.06
33	MSEV(T=40)	-7.71%	-1.97	66	HAMSED(T=50)	-10.82%	-2.86	99	MIN	-33.42%	-6.12