IMPROVEMENT OF VECTOR AUTOREGRESSION (VAR) ESTIMATION USING COMBINE WHITE NOISE (CWN) TECHNIQUE

AGBOLUAJE AYODELE ABRAHAM

DOCTOR OF PHILOSOPHY
UNIVERSITI UTARA MALAYSIA
2018

Awang Had Salleh
Graduate School
of Arts And Sciences

Universiti Utara Malaysia

PERAKUAN KERJA TESIS / DISERTASI
(Certification of thesis / dissertation)

Kami, yang bertandatangan, memperakukan bahawa
(We, the undersigned, certify that)

AGBOLUAJE AYODELE ABRAHAM

calon untuk Ijazah **PhD**
(candidate for the degree of)

telah mengemukakan tesis / disertasi yang bertajuk:
(has presented his/her thesis / dissertation of the following title):

"IMPROVEMENT OF VECTOR AUTOREGRESSION (VAR) ESTIMATION USING COMBINE WHITE NOISE (CWN) TECHNIQUE"

seperti yang tercatat di muka surat tajuk dan kulit tesis / disertasi.
(as it appears on the title page and front cover of the thesis / dissertation).

Bahawa tesis/disertasi tersebut boleh diterima dari segi bentuk serta kandungan dan meliputi bidang ilmu dengan memuaskan, sebagaimana yang ditunjukkan oleh calon dalam ujian lisan yang diadakan pada : ***30 Julai 2017.***
That the said thesis/dissertation is acceptable in form and content and displays a satisfactory knowledge of the field of study as demonstrated by the candidate through an oral examination held on:
July 30, 2017.

Pengerusi Viva: *(Chairman for VIVA)*	Assoc. Prof. Dr. Mohd Kamal Mohd Nawawi	Tandatangan *(Signature)*
Pemeriksa Luar: *(External Examiner)*	Prof. Dr. Azme Khamis	Tandatangan *(Signature)*
Pemeriksa Dalam: *(Internal Examiner)*	Dr. Malina Zulkifli	Tandatangan *(Signature)*
Nama Penyelia/Penyelia-penyelia: *(Name of Supervisor/Supervisors)*	Assoc. Prof. Dr. Suzilah Ismail	Tandatangan *(Signature)*
Nama Penyelia/Penyelia-penyelia: *(Name of Supervisor/Supervisors)*	Dr. Yip Chee Yin	Tandatangan *(Signature)*

Tarikh:
(Date) *July 30, 2017*

Permission to Use

In presenting this thesis in fulfilment of the requirements for a postgraduate degree from Universiti Utara Malaysia, I agree that the Universiti Library may make it freely available for inspection. I further agree that permission for the copying of this thesis in any manner, in whole or in part, for scholarly purpose may be granted by my supervisor(s) or, in their absence, by the Dean of Awang Had Salleh Graduate School of Arts and Sciences. It is understood that any copying or publication or use of this thesis or parts thereof for financial gain shall not be allowed without my written permission. It is also understood that due recognition shall be given to me and to Universiti Utara Malaysia for any scholarly use which may be made of any material from my thesis.

Requests for permission to copy or to make other use of materials in this thesis, in whole or in part, should be addressed to:

Dean of Awang Had Salleh Graduate School of Arts and Sciences
UUM College of Arts and Sciences
Universiti Utara Malaysia
06010 UUM Sintok

Abstrak

Kajian lepas mendedahkan bahawa Autoregresi Eksponen Teritlak Bersyaratkan Heteroskedastik (EGARCH) mengatasi Autoregresi Vektor (VAR) apabila data menunjukkan heteroskedastisiti. Walau bagaimanapun, penganggaran EGARCH tidak cekap apabila data mempunyai kesan keumpilan. Oleh itu, dalam kajian ini, kelemahan VAR dan EGARCH dimodel menggunakan Gabungan Hingar Putih (CWN). Model CWN dibangunkan dengan mengintegrasikan hingar putih VAR dengan EGARCH menggunakan Model Pemurataan Bayesian (BMA) untuk meningkatkan anggaran VAR. Pertama, reja piawai bagi ralat EGARCH (varians heteroskedastik) telah diuraikan menjadi varians sama dan ditakrifkan sebagai siri hingar putih. Kemudian, siri tersebut diubah menjadi model CWN melalui BMA. CWN disahkan menggunakan kajian perbandingan berdasarkan simulasi dan data sebenar Keluaran Dalam Negara Kasar (GDP) bagi empat buah negara. Data disimulasi dengan menggabungkan tiga saiz sampel dengan nilai keumpilan dan kepencongan rendah, sederhana, dan tinggi. Model CWN dibandingkan dengan tiga model sedia ada (VAR, EGARCH dan Purata Bergerak (MA)). Ralat piawai, log-kebolehjadian, kriteria maklumat dan ukuran ralat telahan digunakan untuk menilai prestasi kesemua model tersebut. Dapatan simulasi menunjukkan bahawa CWN mengatasi tiga model yang lain apabila menggunakan saiz sampel 200 dengan keumpilan tinggi dan kepencongan sederhana. Keputusan yang sama diperolehi bagi data sebenar di mana CWN mengatasi tiga model yang lain dengan keumpilan tinggi dan kepencongan sederhana menggunakan GDP Perancis. CWN juga mengatasi tiga model yang lain apabila menggunakan data GDP dari tiga negara lain. CWN merupakan model yang paling tepat dengan anggaran 70 peratus berbanding dengan model VAR, EGARCH dan MA. Dapatan simulasi dan data sebenar ini menunjukkan bahawa CWN adalah lebih tepat dan menyediakan alternatif yang lebih baik untuk memodelkan data heterokedastik dengan kesan keumpilan.

Kata kunci: Autoregresi Eksponen Teritlak Bersyaratkan Heteroskedastik, Autoregresi Vektor, Kesan Keumpilan, Model Pemurataan Bayesian, Gabungan Hingar Putih.

Abstract

Previous studies revealed that Exponential Generalized Autoregressive Conditional Heteroscedastic (EGARCH) outperformed Vector Autoregression (VAR) when data exhibit heteroscedasticity. However, EGARCH estimation is not efficient when the data have leverage effect. Therefore, in this study the weaknesses of VAR and EGARCH were modelled using Combine White Noise (CWN). The CWN model was developed by integrating the white noise of VAR with EGARCH using Bayesian Model Averaging (BMA) for the improvement of VAR estimation. First, the standardized residuals of EGARCH errors (heteroscedastic variance) were decomposed into equal variances and defined as white noise series. Next, this series was transformed into CWN model through BMA. The CWN was validated using comparison study based on simulation and four countries real data sets of Gross Domestic Product (GDP). The data were simulated by incorporating three sample sizes with low, moderate and high values of leverages and skewness. The CWN model was compared with three existing models (VAR, EGARCH and Moving Average (MA)). Standard error, log-likelihood, information criteria and forecast error measures were used to evaluate the performance of the models. The simulation findings showed that CWN outperformed the three models when using sample size of 200 with high leverage and moderate skewness. Similar results were obtained for the real data sets where CWN outperformed the three models with high leverage and moderate skewness using France GDP. The CWN also outperformed the three models when using the other three countries GDP data sets. The CWN was the most accurate model of about 70 percent as compared with VAR, EGARCH and MA models. These simulated and real data findings indicate that CWN are more accurate and provide better alternative to model heteroscedastic data with leverage effect.

Keywords: Exponential Generalized Autoregressive Conditional Heteroscedastic, Vector Autoregression, Leverage Effect, Bayesian Model Averaging, Combine White Noise.

Acknowledgement

I give thanks, praises and honour to Almighty God who has been my shield, and endow me with wisdom, understanding, courage and given me the opportunity to witness the completion of the programme. My sincere thanks and appreciation goes to my able, dynamic and hardworking supervisors in persons of Associate Professor Suzilah Ismail and Associate Professor Chee Yin Yip who have read the work, comments and give professional invaluable suggestions to have a qualitative work. Their tolerance, patience, wisdom, encouragement, constructive criticism and support throughout the program have proved positive. Their efforts have made this thesis to be completed. My profound gratitude goes to the Universiti Utara Malaysia, College of Arts and Sciences, and the School of Quantitative Sciences staff members for their quick response to my academic needs. I appreciate the spirit of cooperation, encouragement and mutual understanding of both the local and international postgraduate students of Universiti Utara Malaysia that are from various parts of the world. Special thanks to Universiti Utara Malaysia Nigerian Community for their understanding and spirit of cooperation. I thank the FGC Changlun fellowship members for their prayers and support, particularly the minister of God for his unrelenting effort to meet our physical and spiritual needs. My special appreciation goes to the TETFund intervention and Ibrahim Badamasi Babangida University, Lapai, Niger State, Nigeria for the fund given for the purpose of this programme. I appreciate the academic and non-academic staff of Mathematics and Computer Science of Ibrahim Badamasi Babangida University, Lapai for their full support during the time of study. Thanks to my parents Chief Agboluaje Olajide and late Mrs. Oyinlola Agboluaje, my younger sisters and brother for their patience and prayers. Special thanks to my dear wife Mrs. Agboluaje Rachael Olubunmi for her care, endurance, cooperation, encouragement and prayers. I appreciate my wonderful children Miss Oyinlola E. Agboluaje, Miss Sarah M. Agboluaje and master Ayokunle I. Agboluaje for their endurance, cooperation, encouragement and prayers. I thank every person that has contributed in a way to make this programme a success. I wish all God blessings.

List of Publications

Agboluaje, A. A., Ismail, S., & Yip, C. Y. (2015). Modelling the error term by moving average and generalized autoregressive conditional heteroscedasticity processes. *American Journal of Applied Sciences*, 12(11), 896. DOI :10.3844/ajassp.2015.896.901

Agboluaje, A.A., Ismail, S., & Yip, C. Y. (2016). Modelling the heteroscedasticity in data distribution. *Global Journal of Pure and Applied Mathematics*, 12(1), 313-322. http://www.ripublication.com

Agboluaje, A. A., Ismail, S.& Yip, C. Y. (2016). Modelling the asymmetric in conditional variance. *Asian Journal of Scientific Research*, 9(2), 39. http://www.scialert.net

Agboluaje, A. A., Ismail, S., & Yip, C. Y. (2016). Comparing vector autoregressive (VAR) estimation with combine white noise (CWN) estimation. *Research Journal of Applied Sciences, Engineering and Technology*, 12(5), 544-549.DOI:10.19026/rjaset.12.2682

Agboluaje, A. A., Ismail, S., & Yip, C. Y. (2016). Evaluating combine white noise with US and UK GDP quarterly data. *Gazi University Journal of Science*, 29(2), 365-372. http://dergipark.gov.tr/gujs

Agboluaje, A. A., Ismail, S., & Yip, C. Y. (2016). Validation of combine white noise using simulated data. *International Journal of Applied Engineering Research*, 11(20), 10125-10130. http://www.ripublication.com

Agboluaje, A. A., Ismail, S., & Yip, C. Y. (2016). Modelling the error term of Australia gross domestic product. *Journal of Mathematics and Statistics*, 12 (4), 248-254. DOI : 10.3844/jmssp.2016.248.254

Agboluaje, A. A., Ismail, S., & Yip, C. Y. (2016). Modelling the error term of regression by combine white noise published in the proceedings of 5th *International Conference on Recent Trends In Engineering, Science and Management* (ICRTESM),Pune, India, December 9 – 10, 2016. www.ijarse.com

Agboluaje, A. A., Ismail, S., & Yip, C. Y. (2016). Modelling the asymmetric volatility with combine white noise across Australia and United Kingdom GDP data set. *Research Journal of Applied Sciences*, 11(11), 1427-1431, 2016. DOI: 10.3923/rjasci.2016.1427.1431

Table of Contents

List of Tables

List of Figures

List of Abbreviations

AC	autocorrelation
ACF	autocorrelation function
ADF	Augmented Dickey-Fuller
AIC	Akaike information criterion
AR	autoregression
ARCH	autoregressive conditional heteroscedastic
ARIMA	autoregressive integrated moving average
ARMA	autoregressive moving average
ARMAX	autoregressive moving average including predetermined variables
AU	Australia
BAMSE	Bartlett's m specification error test
BHHH	Berndt, Hall, Hall and Hausman
BIC	Bayesian information criterion
BMA	Bayesian model averaging
CARMA	controlled autoregressive moving average
CWN	combine white noise
DSGE	dynamic stochastic general equilibrium
EGARCH	exponential generalized autoregressive conditional heteroscedastic
EIV	error in variables
FAVAR	factor-augmented vector autoregression
GARCH	generalized autoregressive conditional heteroscedastic
GDP	gross domestic product
GNP	gross national product
GRMSE	geometric root mean square error
HC2	heteroscedasticity consistent 2
HC3	heteroscedasticity consistent 3
HCCM	heteroscedasticity consistent covariance matrix
HCCME	heteroscedasticity consistent covariance matrix estimator
HVI	heteroscedasticity variance index

IGARCH	integrated generalized autoregressive conditional heteroscedastic
ICC	intraclass correlation coefficient
LIML	limited information maximum likelihood
LOO	leave-one-out
LR	likelihood ratio
MA	moving average
MAE	mean absolute error
MAPE	mean absolute percentage error
MAR	moving average representation
MEM-GARCH	multiplicative error model generalized autoregressive conditional heteroscedastic
MLE	maximum likelihood estimation
OLS	ordinary least square
PAC	partial autocorrelation function
PMB	posterior model probability
PMW	posterior model weight
QMLE	quasi-maximum likelihood estimator
RBC	real business cycle
RCCNMA	random coefficient complex non-linear moving average
RCMA	random coefficient moving average
RESET	regression specification error test
RLA	robust latent autoregression
RMSE	root mean square error
SARIMA	seasonal autoregressive integrated moving average
SSE	sum of square error
STBL	survey of terms of business lending
SVAR	structural vector autoregression
TGARCH	threshold generalized autoregressive conditional heteroscedastic
UK	United Kingdom
US	United States
VAR	vector autoregression

VARX	vector autoregression including predetermined variables
VMA	vector moving average
WMD	weighted minimum distance
WMDF	weighted minimum distance fuller-modified version

CHAPTER ONE

INTRODUCTION

1.1 Background of the Study

Sims (1980) introduced Vector Autoregression (VAR) models that provide macro econometric system a better execution of the models as choices to simultaneous equations with error term called white noise (Harvey). A univariate autoregression is defined as a single-variable model in which the current estimation of a variable is clarified by its lagged values. A VAR is a *k*-equation, *k*-variable direct model in which every variable is regressed by its personal lagged values, in addition to present and past estimations of the left over *k-1* variable. VAR accompany the certification of giving a consistent and dependable methodology to information, interpretation, forecasting, structural inference and policy examination. The tools that accompany VAR are not difficult to use and interpret, to capture the rich dynamics in various time series.

VAR consist of three forms; reduced, recursive and structural (Stock & Watson, 2001). The reduced form VAR passes on that each variable in the model serve as a direct capacity of its own past qualities together with all different variables past values that are measured and a serially uncorrelated error term called white noise. Regression of ordinary least squares is utilized for the estimation of every model. The surprise activities in the variables are the error terms in the regression model following the consideration of its previous values. The reduced structure model that contains error terms shall be connected crosswise over equations, when diverse variables are joined

The contents of the thesis is for internal user only

REFERENCES

Ahmed, M., Aslam, M., & Pasha, G. R. (2011). Inference under heteroscedasticity of unknown form using an adaptive estimator. *Communications in Statistics - Theory and Methods*, *40*(24), 4431–4457. doi.org/10.1080/03610926.2010.513793

Almeida, D. D., & Hotta, L. K. (2014). The leverage effect and the asymmetry of the error distribution in GARCH-based models: the case of Brazilian market related series. *Pesquisa Operacional*, *34*(2), 237-250. doi.org/10.1590/0101-7438.2014.034.02.0237

Altunbas, Y., Gambacorta, L., & Marques-Ibanez, D. (2010). Bank risk and monetary policy. *Journal of Financial Stability*, *6*(3), 121-129. doi.org/10.1016/j.jfs.2009.07.001

Angeloni, I., Faia, E., & Lo Duca, M. (2010). Monetary policy and risk taking. Bruegel Working Paper 2010/00, February 2010. http://www.bruegel.org/publications/publication-de...

Antoine, B., & Lavergne, P. (2014). Conditional moment models under semi-strong identification. *Journal of Econometrics*, *182*(1), 59-69. doi.org/10.1016/j.jeconom.2014.04.008

Armstrong, J. S., & Collopy, F. (1992). Error measures for generalizing about forecasting methods: Empirical comparisons. *International journal of forecasting*, *8*(1), 69-80.doi.org/10.1016/0169-2070(92)90008-W

Asatryan, Z., & Feld, L. P. (2015). Revisiting the link between growth and federalism: A Bayesian model averaging approach. *Journal of Comparative Economics*, *43*(3), 772-781.doi.org/10.1016/j.jce.2014.04.005

Atabaev, N., & Ganiyev, J. (2013). VAR Estimation of the Monetary Transmission Mechanism in Kyrgyzstan. *Eurasian Journal of Business and Economics*, *6*(11), 121–134.

Bates, J. M., & Granger, C. W. (1969). The combination of forecasts. *Journal of the Operational Research Society*, *20*(4), 451-468. DOI: 10.1057/jors.1969.103

Bates, D., Maechler, M., Bolker, B., & Walker, S. (2014). lme4: Linear mixed-effects models using Eigen and S4. *R package version*, *1*(7).

Bast, A., Wilcke, W., Graf, F., Lüscher, P., & Gärtner, H. (2015). A simplified and rapid technique to determine an aggregate stability coefficient in coarse grained soils. *Catena*, *127*, 170-176.doi.org/10.1016/j.catena.2014.11.017

Bernanke, B. S. (1986, November). Alternative explanations of the money-income correlation. In *Carnegie-rochester conference series on public policy* (Vol. 25, pp. 49-99). North-Holland.doi.org/10.1016/0167-2231(86)90037-0

Bernanke, B. S., & Blinder, A. S. (1992). The federal funds rate and the channels of monetary transmission. *The American Economic Review*, 901-921. http://www.jstor.org/stable/2117350

Bernanke, B. S., & Mihov, I. (1998, December). The liquidity effect and long-run neutrality. In *Carnegie-Rochester conference series on public policy* (Vol. 49, pp. 149-194). North-Holland. doi.org/10.1016/S0167-2231(99)00007-X

Berument, H., Metin-Ozcan, K., & Neyapti, B. (2001). Modelling inflation uncertainty using EGARCH: An application to Turkey. *Federal Reserve Bank of Louis Review*, *66*, 15-26.

Blanchard, O. J. (1989). A traditional interpretation of macroeconomic fluctuations. *The American Economic Review*, 1146-1164. http://www.jstor.org/stable/1831442

Blanchard, O. J., & Quah, D. (1989). The dynamic effects of aggregate demand and supply disturbances. *The American Economic Review*, 79(4), 655-673. http://www.jstor.org/stable/1827924

Blaskowitz, O., & Herwartz, H. (2014). Testing the value of directional forecasts in the presence of serial correlation. *International Journal of Forecasting*, *30*(1), 30–42. doi.org/10.1016/j.ijforecast.2013.06.001

Bollerslev, T. (1986). Generalized autoregressive conditional heteroscedasticity. *Journal of econometrics*, *31*(3), 307-327. doi.org/10.1016/0304-4076(86)90063-1

Bollerslev, T. (1987). A conditionally heteroscedastic time series model forspeculative prices and rates of return. *The review of economics and statistics*, 542-547.DOI: 10.2307/1925546

Boos, D. D., & Brownie, C. (2004). Comparing variances and other measures of dispersion. *Statistical Science*, 571-578. http://www.jstor.org/stable/4144427

Bowerman, B.C., O'Connell, R.T., & Koehler, A.B. (2005). *Forecasting, Time series, and Regression.* An applied approach 4th edition. USA Thomson Brooks/Cole.

Box, G. E., & Pierce, D. A. (1970). Distribution of residual autocorrelations in autoregressive-integrated moving average time series models. *Journal of the American statistical Association*, *65*(332), 1509-1526. http://www.jstor.org/stable/2284333

Breese, J. S., Heckerman, D., & Kadie, C. (1998, July). Empirical estimation of predictive algorithms for collaborative filtering. In *Proceedings of the Fourteenth conference on Uncertainty in artificial intelligence* (pp. 43-52). Morgan Kaufmann Publishers Inc.San Francisco, CA, USA.

Breusch, T. S., & Pagan, A. R. (1979). A simple test for heteroscedasticity and random coefficient variation. *Econometrica: Journal of the Econometric Society*, 1287-1294.DOI: 10.2307/1911963

Bulmer, M. G. (1979). *Principles of Statistics*. New York, NY: Dover Publications.

Buch, C. M., Eickmeier, S., & Prieto, E. (2014). In search for yield? Survey-based evidence on bank risk taking. *Journal of Economic Dynamics and Control*, *43*, 12-30. doi.org/10.1016/j.jedc.2014.01.017

Caceres, A., Hall, D. L., Zelaya, F. O., Williams, S. C., & Mehta, M. A. (2009). Measuring fMRI reliability with the intra-class correlation coefficient. *Neuroimage*, *45*(3), 758-768. doi.org/10.1016/j.neuroimage.2008.12.035

Canova, F., & De Nicoló, G. D. (2002). Monetary disturbances matter for business fluctuations in the G-7. *Journal of Monetary Economics*, *49*(6), 1131-1159. doi.org/10.1016/S0304-3932(02)00145-9

Canova, F., & Pappa, E. (2007). Price Differentials in Monetary Unions: The Role of Fiscal Shocks*. *The Economic Journal*, *117*(520), 713-737. **DOI:** 10.1111/j.1468-0297.2007.02047.x

Canova, F., & Paustian, M. (2011). Business cycle measurement with some theory. *Journal of Monetary Economics*, *58*(4), 345-361. doi.org/10.1016/j.jmoneco.2011.07.005

Chai, T., & Draxler, R. R. (2014). Root mean square error (RMSE) or mean absolute error (MAE)?–Arguments against avoiding RMSE in the literature. *Geoscientific Model Development*, *7*(3), 1247-1250. doi:10.5194/gmd-7-1247-2014

Chao, J. C., Hausman, J. A., Newey, W. K., Swanson, N. R., & Woutersen, T. (2014). Testing over identifying restrictions with many instruments and heteroscedasticity. *Journal of Econometrics*, *178*, 15–21. DOI: 10.1016/j.jeconom.2013.08.003

Charemza, W.W. & Deadman, D. F. (1992). *New directions in econometric practice*, 1st edition. Cheltenham, UK. Edward Elger Publishing limited.

Charemza, W.W. & Deadman, D. F. (1997). *New directions in econometric practice*, 2nd edition. Cheltenham UK. Edward Elger Publishing limited.

Chaudhuri, K., Kakade, S. M., Netrapalli, P., & Sanghavi, S. (2015, December). Convergence Rates of Active Learning for Maximum Likelihood Estimation. In *Advances in Neural Information Processing Systems*28 (pp. 1090-1098).Montreal, Canada

Christ, C. F. (1994). The Cowles Commission's Contributions to Econometrics at Chicago, 1939-1955. *Economic literature*, 32(1), 30-59. http://www.jstor.org/stable/2728422

Christiano, L. J., Eichenbaum, M., & Evans, C. L. (1996). Sticky price and limited participation models of money: A comparison. *European Economic Review*, *41*(6), 1201-1249.doi.org/10.1016/S0014-2921(97)00071-8

Cooley, T. F., & LeRoy, S. F. (1985). Atheoretical macroeconometrics: a critique. *Journal of Monetary Economics*, *16*(3), 283-308. doi.org/10.1016/0304-3932(85)90038-8

Cribari-Neto, F., & Galvão, N. M. S. (2003). A Class of Improved Heteroscedasticity-Consistent Covariance Matrix Estimators. *Communications in Statistics - Theory and Methods*, *32*(10), 1951–1980. doi.org/10.1081/STA-120023261

Cushman, D. O., & Zha, T. (1997). Identifying monetary policy in a small open economy under flexible exchange rates. *Journal of Monetary economics*, *39*(3), 433-448.doi.org/10.1016/S0304-3932(97)00029-9

De Nicolo, G., Dell'Ariccia, G., Laeven, L., & Valencia, F. (2010). Monetary Policy and Bank Risk Taking. doi.org/10.2139/ssrn.1654582

Dedola, L., & Neri, S. (2007b). What does a technology shock do? A VAR estimation with model-based sign restrictions. *Journal of Monetary Economics*, *54*(2), 512–549. doi.org/10.1016/j.jmoneco.2005.06.006

Ding, F., & Chen, T. (2005). Identification of Hammerstein nonlinear ARMAX systems. *Automatica*, *41*(9), 1479-1489. doi.org/10.1016/j.automatica.2005.03.026

Dovonon, P., & Renault, E. (2013). Testing for Common Conditionally Heteroscedastic Factors. *Econometrica*, *81*(6), 2561-2586. **DOI:** 10.3982/ECTA10082

Durbin, J. (1959). Efficient Estimation of Parameters in Moving-Average Models. *Biometrica Trust*, 46(3/4), 306-316. DOI: 10.2307/2333528

Eickmeier, S., & Hofmann, B. (2013). Monetary policy, housing booms, and financial (im) balances. *Macroeconomic dynamics*, *17*(04), 830-860. DOI: https://doi.org/10.1017/S1365100511000721

Engle, R. F. (1982). Autoregressive conditional heteroscedasticity with estimates of the variance of United Kingdom inflation. *Econometrica: Journal of the Econometric Society*, 987-1007.DOI: 10.2307/1912773

Engle, R. F. (1983). Estimates of the Variance of US Inflation Based upon the ARCH Model. *Journal of Money, Credit and Banking*, 286-301. DOI: 10.2307/1992480

Engle, R. (2001). GARCH 101: The use of ARCH/GARCH models in applied econometrics. *The Journal of Economic Perspectives*, *15*(4), 157-168. http://www.jstor.org/stable/2696523

Engsted, T., & Pedersen, T. Q. (2014). Bias-correction in vector autoregressive models: A simulation study. *Econometrics*, *2*(1), 45-71. doi:10.3390/econometrics2010045

Ewing, B. T., & Malik, F. (2013). Volatility transmission between gold and oil futures under structural breaks. *International Review of Economics & Finance*, *25*, 113-121. doi.org/10.1016/j.iref.2012.06.008

Faust, J. (1998, December). The robustness of identified VAR conclusions about money. In *Carnegie-Rochester Conference Series on Public Policy* (Vol. 49, pp. 207-244). North-Holland.doi.org/10.1016/S0167-2231(99)00009-3

Fildes, R. (1992). The evaluation of extrapolative forecasting methods. *International Journal of Forecasting*, *8*(1), 81-98. doi.org/10.1016/0169-2070(92)90009-X

Fildes, R., Wei, Y., & Ismail, S. (2011). Evaluating the forecasting performance of econometric models of air passenger traffic flows using multiple error measures. *International Journal of Forecasting*, *27*(3), 902-922. doi.org/10.1016/j.ijforecast.2009.06.002

Fisher, D., Hildrum, K., Hong, J., Newman, M., Thomas, M., & Vuduc, R. (2000, July). SWAMI (poster session): a framework for collaborative filtering algorithm development and evaluation. In *Proceedings of the 23rd annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 366-368). ACM. New York, NY: doi>10.1145/345508.345658

Francis, N., Owyang, M. T., Roush, J. E., & DiCecio, R. (2014). A flexible finite-horizon alternative to long-run restrictions with an application to technology shocks. *Review of Economics and Statistics*, *96*(4), 638-647. doi:10.1162/REST_a_00406

Friedman, M., & Schwartz, A. J. (Eds.). (1982). The role of money. In *Monetary Trends in the United States and United Kingdom: Their Relation to Income, Prices, and Interest Rates, 1867-1975* (pp. 621-632). University of Chicago Press.http://www.nber.org/chapters/c11412

Fujita, S. (2011). Dynamics of worker flows and vacancies: evidence from the sign restriction approach. *Journal of Applied Econometrics*, *26*(1), 89-121. **DOI:** 10.1002/jae.1111

Godfrey, L. G. (1978). Testing for higher order serial correlation in regression equations when the regressors include lagged dependent variables. *Econometrica: Journal of the Econometric Society*, 1303-1310. DOI: 10.2307/1913830

Gordon, D. B., & Leeper, E. M. (1994). The dynamic impacts of monetary policy: an exercise in tentative identification. *Journal of Political Economy*, 1228-1247. DOI: 10.1086/261969

Greene, W. H. (2008). The econometric approach to efficiency analysis. *The measurement of productive efficiency and productivity growth*, *1*, 92-250.

Gregory, A. W., & Smith, G. W. (1995). Business cycle theory and econometrics. *The Economic Journal*, 1597-1608.DOI: 10.2307/2235121

Günnemann, N., Günnemann, S., & Faloutsos, C. (2014, April). Robust multivariate autoregression for anomaly detection in dynamic product ratings. In *Proceedings of the 23rd international conference on World wide web* (pp. 361-372). International World Wide Web Conferences Steering Committee.ACMNew York, NY:doi>10.1145/2566486.2568008

Hall, M. (2007). A decision tree-based attribute weighting filter for naive Bayes.*Knowledge-Based Systems*, *20*(2), 120-126. doi.org/10.1016/j.knosys.2006.11.008

Harvey, A. C. (1993). *Time series models* 2nd edition. The MIT Press. Cambridge. Massachusetts. Harvester Wheatsheaf Publisher.

Harvey, A. C. & Philips, G. D. A. (1979). Maximum Likelihood Estimation of Regression Models with Autoregressive- Moving Average Disturbances. *Biometrica Trust*, 66(1), 49-58. doi.org/10.1093/biomet/66.1.49

Harvey, A., & Sucarrat, G. (2014). EGARCH models with fat tails, skewness and leverage. *Computational Statistics & Data Estimation*, *76*, 320-338. doi.org/10.1016/j.csda.2013.09.022

Hassan, M., Hossny, M., Nahavandi, S., & Creighton, D. (2012, March). Heteroscedasticity variance index. In *Computer Modelling and Simulation (UKSim), 2012 UKSim 14th International Conference on* (pp. 135-141). IEEE. **DOI:** 10.1109/UKSim.2012.28

Hassan, M., Hossny, M., Nahavandi, S., & Creighton, D. (2013, April). Quantifying Heteroscedasticity Using Slope of Local Variances Index. In *Computer Modelling and Simulation (UKSim), 2013 UKSim 15th International Conference on* (pp. 107-111). IEEE.**DOI:** 10.1109/UKSim.2013.75

Hentschel, L. (1995). All in the family nesting symmetric and asymmetric GARCH models. *Journal of Financial Economics*, *39*(1), 71-104. doi.org/10.1016/0304-405X(94)00821-H

Herlocker, J. L., Konstan, J. A., Borchers, A., & Riedl, J. (1999, August). An algorithmic framework for performing collaborative filtering. In *Proceedings of the 22nd annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 230-237). ACM.New York, NY: doi>10.1145/312624.312682

Higgins, M. L., & Bera, A. K. (1992). A class of nonlinear ARCH models. *International Economic Review*, 137-158.DOI: 10.2307/2526988

Hoeting, J. A., Madigan, D., Raftery, A. E., & Volinsky, C. T. (1999). Bayesian model averaging: a tutorial. *Statistical science*, 382-401. http://www.jstor.org/stable/2676803

Hofmann, T., & Puzicha, J. (1999, July). Latent class models for collaborative filtering. *IJCAI'99 Proceedings of the 16th international joint conference on Artificial intelligence*- Volume 2. pp. 688-693.Morgan Kaufmann Publishers Inc. San Francisco, CA, USA

Hooten, M. B., & Hobbs, N. T. (2015). A guide to Bayesian model selection for ecologists. *Ecological Monographs*, *85*(1), 3-28.**DOI:** 10.1890/14-0661.1

Hu, P., & Ding, F. (2013). Multistage least squares based iterative estimation for feedback nonlinear systems with moving average noises using the hierarchical identification principle. *Nonlinear Dynamics*, *73*(1-2), 583-592. DOI 10.1007/s11071-013-0812-0

Inoue, A., & Kilian, L. (2013). Inference on impulse response functions in structuralVAR models. *Journal of Econometrics*, *177*(1), 1-13. doi.org/10.1016/j.jeconom.2013.02.009

Jin, R., Chai, J. Y., & Si, L. (2004, July). An automatic weighting scheme for collaborative filtering. In *Proceedings of the 27th annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 337-344). ACM New York, NY: doi>10.1145/1008992.1009051

Kaplan, D., & Chen, J. (2014). Bayesian model averaging for propensity score estimation. *Multivariate Behavioral Research*, *49*, 505-517. doi.org/10.1080/00273171.2014.928492

Kelejian, H. H. & Oates, W. E. (1981). *Introduction to econometrics principles and applications* 2nd edition. New York, NY: Harper and Row, Publishers

Kennedy, P. (2008). *A guide to econometrics* 6th edition. Blackwell Publishing. www.wiley.com

Kilian, L., & Murphy, D. P. (2012). Why agnostic sign restrictions are not enough: understanding the dynamics of oil market VAR models. *Journal of the European Economic Association*, *10*(5), 1166-1188. **DOI:** 10.1111/j.1542-4774.2012.01080.x

Kilian, L., & Murphy, D. P. (2014). The role of inventories and speculative trading in the global market for crude oil. *Journal of Applied Econometrics*, *29*(3), 454-478. DOI: 10.1002/jae.2322

Kydland, F. E., & Prescott, E. C. (1991). The econometrics of the general equilibrium approach to business cycles. *The Scandinavian Journal of Economics*, 161-178.DOI: 10.2307/3440324

Lang, W. W., & Nakamura, L. I. (1995). 'Flight to quality' in banking and economic activity. *Journal of Monetary Economics*, *36*(1), 145-164. doi.org/10.1016/0304-3932(95)01204-9

Lazim, M. A. (2013). *Introductory business forecasting. A practical approach* 3rd edition. Printed in Kuala Lumpur, Malaysia:Penerbit Press, University Technology Mara

Li, L., Zeng, L., Lin, Z. J., Cazzell, M., & Liu, H. (2015). Tutorial on use of intraclass correlation coefficients for assessing intertest reliability and its application in functional near-infrared spectroscopy–based brain imaging. *Journal of biomedical optics*, *20*(5), 050801-050801. doi:10.1117/1.JBO.20.5.050801

Lim, T.-S. & Loh, W.-Y. (1996). A comparison of tests of equality of variances. *Computational Statistics and Data Estimation*, 22, 287-301. doi.org/10.1016/0167-9473(95)00054-2

Link, W. A., & Barker, R. J. (2006). Model weights and the foundations ofmultimodel inference. *Ecology*, *87*(10), 2626-2635. DOI: 10.1890/0012-9658(2006)87[2626:MWATFO]2.0.CO;2

Lippi, M., & Reichlin, L. (1993). The dynamic effects of aggregate demand andsupply disturbances: Comment. *The American Economic Review*, 644-652. http://www.jstor.org/stable/2117539

Liu, T. C. (1960). Under identification, structural estimation, and forecasting. *Econometrica: Journal of the Econometric Society*, 855-865. DOI: 10.2307/1907567

Lu, L., & Shara, N. (2007). Reliability estimation: Calculate and compare intra-class correlation coefficients (ICC) in SAS. *Northeast SAS Users Group*, *14*.xa.yimg.comf

Lütkepohl, H. (2006). *Structural vector autoregressive estimation for cointegrated variables* (pp. 73-86). Springer Berlin Heidelberg.New York **DOI:**10.1007/3-540-32693-6_6

Marek, T. (2005). On invertibility of a random coefficient moving average model. *Kybernetika*, *41*(6), 743-756.http://dml.cz/dmlcz/135690

Martinet, G. G., & McAleer, M. (2016). On the Invertibility of EGARCH (p, q). *Econometric Reviews*, 1-26.doi.org/10.1080/07474938.2016.1167994

McAleer, M. (2014). Asymmetry and Leverage in Conditional Volatility Models. *Econometrics*, *2*(3),145-150. doi:10.3390/econometrics2030145

McAleer, M., & Hafner, C. M. (2014). A one line derivation of EGARCH. *Econometrics*, *2*(2),92-97. doi:10.3390/econometrics2020092

McGraw, K. O., & Wong, S. P. (1996). Forming inferences about some intraclass correlation coefficients. *Psychological methods*, *1*(1), 30. doi.org/10.1037/1082-989X.1.1.30

Mountford, A., & Uhlig, H. (2009). What are the effects of fiscal policy shocks?. *Journal of applied econometrics*, *24*(6), 960-992.**DOI:** 10.1002/jae.1079

Mutunga, T. N., Islam, A. S., & Orawo, L. A. O. (2015). Implementation of the estimating functions approach in asset returns volatility forecasting using first order asymmetric GARCH models. *Open Journal of Statistics*, *5*(05), 455.DOI:10.4236/ojs.2015.55047

Myung, I. J. (2003). Tutorial on maximum likelihood estimation. *Journal of mathematical Psychology*, *47*(1), 90-100.doi.org/10.1016/S0022-2496(02)00028-7

Nelson, D. B. (1991). Conditional heteroscedasticity in asset returns: A new approach. *Econometrica: Journal of the Econometric Society*, 347-370. DOI: 10.2307/2938260

Newbold, P. and Granger, C. W. J. (1974). Experience with Forecasting Univariate Time Series and the Combination of Forecasts. *Journal of the Royal Statistical Society*, *137*(2), 131–165.DOI: 10.2307/2344546

Ng, A. Y., & Jordan, M. I. (2002). On discriminative vs. generative classifiers: Acomparison of logistic regression and naive bayes. *Advances in neural information processing systems*, *2*, 841-848.

Ng, H. S., & Lam, K. P. (2006, October). How Does Sample Size Affect GARCH Models?. In *JCIS*.

Pappa, E. (2009). The effects of fiscal shocks on employment and the real wage. *International economic review***,** 50(1). **DOI:** 10.1111/j.1468-2354.2008.00528.x

Park, B. U., Simar, L., & Zelenyuk, V. (2015). Categorical data in local maximum likelihood: theory and applications to productivity analysis. *Journal of Productivity Analysis*, *43*(2), 199-214.doi:10.1007/s11123-014-0394-y

Paruolo, P., & Rahbek, A. (1999). Weak exogeneity in I (2) VAR systems. *Journal of Econometrics*, *93*(2), 281-308.doi.org/10.1016/S0304-4076(99)00012-3

Pennock, D. M., Horvitz, E., Lawrence, S., & Giles, C. L. (2000, June). Collaborative filtering by personality diagnosis: A hybrid memory-and model-based approach. In *Proceedings of the Sixteenth conference on Uncertainty in artificial intelligence* (pp. 473-480). Morgan Kaufmann Publishers Inc. San Francisco, CA, USA.

Piovesana, A., & Senior, G. (2016). How Small Is Big Sample Size and Skewness. *Assessment*.DOI: 10.1177/1073191116669784

Qin, D. & Gilbert, C. L. (2001). The error term in the history of time series econometrics. *Econometric theory*, 17, 424-450. Cambridge University Press

Quah, D. T. (1995). Business Cycle Empirics: Calibration and Estimation. *The Economic*, 105(433).1594-1596. DOI: 10.2307/2235120

Raftery, A. E. (1995). Bayesian model selection in social research. *Sociological methodology*, 111-163.DOI: 10.2307/271063

Raftery, A. E., & Painter, I. S. (2005). BMA: An R package for Bayesian model averaging. *R news*, *5*(2), 2-8.

Rajan, R. G. (2006). Has finance made the world riskier? *European Financial Management*, *12*(4), 499-533. **DOI:** 10.1111/j.1468-036X.2006.00330.x

Ramsey, J. B. (1969). Tests for specification errors in classical linear least-squares regression estimation. *Journal of the Royal Statistical Society. Series B (Methodological)*, 350-371.http://www.jstor.org/stable/2984219

Resnick, P., Iacovou, N., Suchak, M., Bergstrom, P., & Riedl, J. (1994, October). Group Lens: an open architecture for collaborative filtering of netnews. In *Proceedings of the 1994 ACM conference on Computer supported cooperative work* (pp. 175-186). ACMNew York, NY: doi>10.1145/192844.192905

Rodrıguez, G., & Elo, I. (2003). Intra-class correlation in random-effects models for binary data. *The Stata Journal*, *3*(1), 32-46

Rodríguez, M. J., & Ruiz, E. (2012). Revisiting several popular GARCH models with leverage effect: Differences and similarities. *Journal of Financial Econometrics*, *10*(4), 637-668.**DOI:** https://doi.org/10.1093/jjfinec/nbs003

Sargent, T. J., & Sims, C. A. (1977). Business cycle modelling without pretending tohave too much a priori economic theory. *New methods in business cycle research*,*1*, 145-168.

Savolainen, P. T., Mannering, F. L., Lord, D., & Quddus, M. A. (2011). The statistical estimation of highway crash-injury severities: A review and assessment of methodological alternatives. *Accident Estimation & Prevention*, *43*(5), 1666-1676.doi.org/10.1016/j.aap.2011.03.025

Scholl, A., & Uhlig, H. (2008). New evidence on the puzzles: Results from agnostic identification on monetary policy and exchange rates. *Journal of International Economics*, *76*(1), 1-13.doi.org/10.1016/j.jinteco.2008.02.005

Shao, K., & Gift, J. S. (2014). Model uncertainty and Bayesian model averaged benchmark dose estimation for continuous data. *Risk Estimation*, *34*(1), 101-120. DOI: 10.1111/risa.12078.

Si, L. & Jin, R. (2003). Flexible Mixture Model for Collaborative Filtering. In *Uncertainty in artificial intelligence* (pp. 704–711). CML.

Sims, C. A. (1980). Macroeconomics and Reality, *Econometrica*, *48*(1), 1–48. DOI: 10.2307/1912017

Sims, C. A. (1986). Are forecasting models usable for policy estimation? *Federal Reserve Bank of Minneapolis Quarterly Review*, *10*(1), 2-16. http://www.minneapolisfed.org/publications_papers/pub_display.cfm?id=186

Sims, C. A., & Zha, T. A. O. (2006). Does monetary policy generate recessions? *Macroeconomic Dynamics*, *10*, 231–272. DOI: https://doi.org/10.1017/S136510050605019X

Snipes, M., & Taylor, D. C. (2014). Model selection and Akaike Information Criteria: An example from wine ratings and prices. *Wine Economics and Policy*, *3*(1), 3-9. http://dx.doi.org/10.1016/j.wep.2014.03.001

Soboroff, I., & Nicholas, C. (2000, July). Collaborative filtering and the generalized vector space model (poster session). In *Proceedings of the 23rd annual international ACM SIGIR conference on Research and development in information retrieval* (pp. 351-353). ACM New York, NY: doi>10.1145/345508.345646

Spiegelhalter, D. J., Best, N. G., Carlin, B. P., & Linde, A. (2014). The deviance information criterion: 12 years on. *Journal of the Royal Statistical Society: Series B (Statistical Methodology)*, *76*(3), 485-493.**DOI:** 10.1111/rssb.12062

Stanford, D. C., & Raftery, A. E. (2002). Approximate Bayes factors for image segmentation: The pseudolikelihood information criterion (PLIC). *IEEE Transactions on Pattern Estimation and Machine Intelligence*, *24*(11), 1517-1520.**DOI:** 10.1109/TPAMI.2002.1046170

Stapleton, J. H. (2009). *Linear statistical models* (2nd edition). John Wiley & Sons. New York.www.wiley.com

Stock, J. H., & Watson, M. W. (2001). Vector autoregressions. *Journal of Economic perspectives*, 101-115.http://www.jstor.org/stable/2696519

Strongin, S. (1995). The identification of monetary policy disturbances explaining the liquidity puzzle. *Journal of Monetary Economics*, *35*(3), 463-497. doi.org/10.1016/0304-3932(95)01197-V

Sucarrat, G. (2013). betategarch: Simulation, estimation and forecasting of Beta-Skew-t-EGARCH Models. *The R Journal*, *5*(2), 137-147. https://**journal**.**r**-project.org/archive/**2013-2**/**sucarrat**

Sucarrat, G., & Sucarrat, M. G. (2013). Package 'betategarch'. http://www.sucarrat.net/

Swamy, V. (2014). Testing the interrelatedness of banking stability measures. *Journal of Financial Economic Policy*, *6*(1), 25-45. doi.org/10.1108/JFEP-01-2013-0002

Tofallis, C. (2015). A better measure of relative prediction accuracy for model selection and model estimation. *Journal of the Operational Research Society*, *66*(8), 1352-1362.doi.org/10.1057/jors.2014.124

Törnqvist, L., Vartia, P., & Vartia, Y. O. (1985). How should relative changes be measured?. *The American Statistician*, *39*(1), 43-46. doi.org/10.1080/00031305.1985.10479385

Uchôa, C. F. A., Cribari-Neto, F., & Menezes, T. A. (2014). Testing inference in heteroscedastic fixed effects models. *European Journal of Operational Research*, *235*(3), 660–670.doi.org/10.1016/j.ejor.2014.01.032

Uhlig, H. (2005). What are the effects of monetary policy on result? Results from an agnostic identification procedure. *Journal of Monetary Economics*, *52*(2), 381–419. doi.org/10.1016/j.jmoneco.2004.05.007

Van Beers, R. J., Van der Meer, Y., & Veerman, R. M. (2013). What autocorrelation tells us about motor variability: Insights from dart throwing. *PloS one*, *8*(5), e64332. doi.org/10.1371/journal.pone.0064332

Vivian, A., & Wohar, M. E. (2012). Commodity volatility breaks. *Journal of International Financial Markets, Institutions and Money*, *22*(2), 395-422. doi.org/10.1016/j.intfin.2011.12.003

Wallis, K. F. (2011). Combining forecasts–forty years later. *Applied Financial Economics*, *21*(1-2), 33-41.doi.org/10.1080/09603107.2011.523179

White, H. (1980). A heteroscedasticity-consistent covariance matrix estimator and a direct test for heteroscedasticity. *Econometrica*, 48 (4), 817-838. DOI: 10.2307/1912934

Williams, R. (2009). Using heterogeneous choice models to compare logit and probit coefficients across groups. *Sociological Methods & Research*, *37*(4), 531-559. http://smr.sagepub.comhttp://online.sagepub.com

Yan, X.& Su, X. G. (2009). *Linear regression estimation: theory and computing*. World Scientific Publishing Co. Pte. Ltd. www.manalhelal.com/Books/geo/**LinearRegression**Analysis**TheoryandComputing**

Yu, K., Wen, Z., Xu, X., & Ester, M. (2001). Feature weighting and instance selection for collaborative filtering. In *Database and Expert Systems Applications, 2001. Proceedings. 12th International Workshop on* (pp. 285-290). IEEE**DOI:** 10.1109/DEXA.2001.953076

Zhang, Z., Jia, J., & Ding, R. (2012). Hierarchical least squares based iterativeestimation algorithm for multivariable Box–Jenkins-like systems using the auxiliary model. *Applied Mathematics and Computation*, *218*(9), 5580–5587. doi.org/10.1016/j.amc.2011.11.051

Appendix A

GDP Real Data

1. Quarterly United States Gross Domestic Product (US GDP) Data for fifty five years

Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP
1960Q1	3123.2	1968Q3	4599.3	1977Q1	5799.2	1985Q3	7655.2
1960Q2	3111.3	1968Q4	4619.8	1977Q2	5913.0	1985Q4	7712.6
1960Q3	3119.1	1969Q1	4691.6	1977Q3	6017.6	1986Q1	7784.1
1960Q4	3081.3	1969Q2	4706.7	1977Q4	6018.2	1986Q2	7819.8
1961Q1	3102.3	1969Q3	4736.1	1978Q1	6039.2	1986Q3	7898.6
1961Q2	3159.9	1969Q4	4715.5	1978Q2	6274.0	1986Q4	7939.5
1961Q3	3212.6	1970Q1	4707.1	1978Q3	6335.3	1987Q1	7995.0
1961Q4	3277.7	1970Q2	4715.4	1978Q4	6420.3	1987Q2	8084.7
1962Q1	3336.8	1970Q3	4757.2	1979Q1	6433.0	1987Q3	8158.0
1962Q2	3372.7	1970Q4	4708.3	1979Q2	6440.8	1987Q4	8292.7
1962Q3	3404.8	1971Q1	4834.3	1979Q3	6487.1	1988Q1	8339.3
1962Q4	3418.0	1971Q2	4861.9	1979Q4	6503.9	1988Q2	8449.5
1963Q1	3456.1	1971Q3	4900.0	1980Q1	6524.9	1988Q3	8498.3
1963Q2	3501.1	1971Q4	4914.3	1980Q2	6392.6	1988Q4	8610.9
1963Q3	3569.5	1972Q1	5002.4	1980Q3	6382.9	1989Q1	8697.7
1963Q4	3595.0	1972Q2	5118.3	1980Q4	6501.2	1989Q2	8766.1
1964Q1	3672.7	1972Q3	5165.4	1981Q1	6635.7	1989Q3	8831.5
1964Q2	3716.4	1972Q4	5251.2	1981Q2	6587.3	1989Q4	8850.2
1964Q3	3766.9	1973Q1	5380.5	1981Q3	6662.9	1990Q1	8947.1
1964Q4	3780.2	1973Q2	5441.5	1981Q4	6585.1	1990Q2	8981.7
1965Q1	3873.5	1973Q3	5411.9	1982Q1	6475.0	1990Q3	8983.9
1965Q2	3926.4	1973Q4	5462.4	1982Q2	6510.2	1990Q4	8907.4
1965Q3	4006.2	1974Q1	5417.0	1982Q3	6486.8	1991Q1	8865.6
1965Q4	4100.6	1974Q2	5431.3	1982Q4	6493.1	1991Q2	8934.4
1966Q1	4201.9	1974Q3	5378.7	1983Q1	6578.2	1991Q3	8977.3
1966Q2	4219.1	1974Q4	5357.2	1983Q2	6728.3	1991Q4	9016.4
1966Q3	4249.2	1975Q1	5292.4	1983Q3	6860.0	1992Q1	9123.0
1966Q4	4285.6	1975Q2	5333.2	1983Q4	7001.5	1992Q2	9223.5
1967Q1	4324.9	1975Q3	5421.4	1984Q1	7140.6	1992Q3	9313.2
1967Q2	4328.7	1975Q4	5494.4	1984Q2	7266.0	1992Q4	9406.5
1967Q3	4366.1	1976Q1	5618.5	1984Q3	7337.5	1993Q1	9424.1
1967Q4	4401.2	1976Q2	5661.0	1984Q4	7396.0	1993Q2	9480.1
1968Q1	4490.6	1976Q3	5689.8	1985Q1	7469.5	1993Q3	9526.3
1968Q2	4566.4	1976Q4	5732.5	1985Q2	7537.9	1993Q4	9653.5

Quarterly United States Gross Domestic Product (US GDP) Data for fifty five years continued

Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP
1994Q1	9748.2	1999Q2	11962.5	2004Q3	13830.8	2009Q4	14541.9
1994Q2	9881.4	1999Q3	12113.1	2004Q4	13950.4	2010Q1	14604.8
1994Q3	9939.7	1999Q4	12323.3	2005Q1	14099.1	2010Q2	14745.9
1994Q4	10052.5	2000Q1	12359.1	2005Q2	14172.7	2010Q3	14845.5
1995Q1	10086.9	2000Q2	12592.5	2005Q3	14291.8	2010Q4	14939.0
1995Q2	10122.1	2000Q3	12607.7	2005Q4	14373.4	2011Q1	14881.3
1995Q3	10208.8	2000Q4	12679.3	2006Q1	14546.1	2011Q2	14989.6
1995Q4	10281.2	2001Q1	12643.3	2006Q2	14589.6	2011Q3	15021.1
1996Q1	10348.7	2001Q2	12710.3	2006Q3	14602.6	2011Q4	15190.3
1996Q2	10529.4	2001Q3	12670.1	2006Q4	14716.9	2012Q1	15275.0
1996Q3	10626.8	2001Q4	12705.3	2007Q1	14726.0	2012Q2	15336.7
1996Q4	10739.1	2002Q1	12822.3	2007Q2	14838.7	2012Q3	15431.3
1997Q1	10820.9	2002Q2	12893.0	2007Q3	14938.5	2012Q4	15433.7
1997Q2	10984.2	2002Q3	12955.8	2007Q4	14991.8	2013Q1	15538.4
1997Q3	11124.0	2002Q4	12964.0	2008Q1	14889.5	2013Q2	15606.6
1997Q4	11210.3	2003Q1	13031.2	2008Q2	14963.4	2013Q3	15779.9
1998Q1	11321.2	2003Q2	13152.1	2008Q3	14891.6	2013Q4	15916.2
1998Q2	11431.0	2003Q3	13372.4	2008Q4	14577.0	2014Q1	15831.7
1998Q3	11580.6	2003Q4	13528.7	2009Q1	14375.0	2014Q2	16010.4
1998Q4	11770.7	2004Q1	13606.5	2009Q2	14355.6	2014Q3	16205.6
1999Q1	11864.7	2004Q2	13706.2	2009Q3	14402.5	2014Q4	16293.7

2. Quarterly United Kingdom Gross Domestic Product (UK GDP) Data for fifty five years

Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP
1960Q1	119158	1968Q3	158159	1977Q1	163732	1985Q3	223107
1960Q2	118220	1968Q4	158979	1977Q2	166606	1985Q4	224158
1960Q3	120089	1969Q1	157884	1977Q3	169572	1986Q1	225834
1960Q4	120819	1969Q2	161652	1977Q4	170207	1986Q2	228391
1961Q1	122782	1969Q3	163263	1978Q1	170314	1986Q3	229928
1961Q2	123267	1969Q4	164771	1978Q2	174840	1986Q4	234262
1961Q3	122633	1970Q1	163732	1978Q3	175260	1987Q1	236229
1961Q4	122412	1970Q2	166606	1978Q4	178032	1987Q2	239505
1962Q1	123001	1970Q3	169572	1979Q1	186968	1987Q3	245364
1962Q2	124166	1970Q4	170207	1979Q2	187241	1987Q4	248254
1962Q3	124919	1971Q1	170314	1979Q3	185345	1988Q1	252941
1962Q4	124416	1971Q2	174840	1979Q4	184558	1988Q2	254603
1963Q1	125097	1971Q3	175260	1980Q1	179528	1988Q3	258558
1963Q2	130461	1971Q4	178032	1980Q2	182105	1988Q4	260772
1963Q3	131075	1972Q1	186968	1980Q3	183246	1989Q1	261846
1963Q4	134096	1972Q2	187241	1980Q4	180483	1989Q2	263514
1964Q1	134864	1972Q3	185345	1981Q1	180603	1989Q3	263651
1964Q2	137228	1972Q4	184558	1981Q2	177509	1989Q4	263719
1964Q3	137740	1973Q1	179528	1981Q3	176931	1990Q1	265371
1964Q4	139872	1973Q2	182105	1981Q4	179080	1990Q2	266644
1965Q1	139483	1973Q3	183246	1982Q1	182043	1990Q3	263704
1965Q2	139602	1973Q4	180483	1982Q2	181669	1990Q4	262665
1965Q3	140784	1974Q1	180603	1982Q3	184000	1991Q1	261838
1965Q4	141663	1974Q2	177509	1982Q4	188037	1991Q2	261442
1966Q1	141872	1974Q3	176931	1983Q1	188138	1991Q3	260779
1966Q2	142667	1974Q4	179080	1983Q2	186977	1991Q4	261240
1966Q3	143183	1975Q1	182043	1983Q3	188264	1992Q1	261346
1966Q4	142577	1975Q2	181669	1983Q4	191472	1992Q2	261067
1967Q1	144536	1975Q3	184000	1984Q1	192949	1992Q3	262816
1967Q2	146529	1975Q4	188037	1984Q2	195341	1992Q4	264742
1967Q3	147194	1976Q1	158159	1984Q3	197898	1993Q1	266762
1967Q4	147960	1976Q2	158979	1984Q4	199843	1993Q2	268180
1968Q1	153354	1976Q3	157884	1985Q1	198861	1993Q3	270418
1968Q2	152761	1976Q4	161652	1985Q2	207589	1993Q4	272389

Quarterly United Kingdom Gross Domestic Product (UK GDP) Data for fifty five years continued

Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP
1994Q1	275836	1999Q2	319560	2004Q3	376942	2009Q4	391685
1994Q2	279116	1999Q3	324767	2004Q4	378470	2010Q1	393678
1994Q3	282336	1999Q4	329111	2005Q1	381142	2010Q2	397525
1994Q4	283840	2000Q1	332555	2005Q2	385058	2010Q3	400096
1995Q1	284637	2000Q2	334960	2005Q3	389023	2010Q4	400195
1995Q2	285751	2000Q3	336221	2005Q4	394268	2011Q1	402341
1995Q3	288862	2000Q4	337211	2006Q1	396566	2011Q2	403260
1995Q4	290247	2001Q1	341026	2006Q2	398553	2011Q3	406068
1996Q1	293666	2001Q2	343637	2006Q3	399251	2011Q4	406008
1996Q2	294490	2001Q3	345468	2006Q4	402258	2012Q1	406283
1996Q3	295521	2001Q4	346546	2007Q1	405329	2012Q2	405560
1996Q4	296474	2002Q1	348115	2007Q2	407767	2012Q3	408938
1997Q1	297909	2002Q2	350978	2007Q3	411205	2012Q4	407557
1997Q2	301318	2002Q3	354058	2007Q4	413131	2013Q1	409985
1997Q3	303490	2002Q4	357286	2008Q1	414424	2013Q2	412620
1997Q4	307560	2003Q1	360733	2008Q2	413465	2013Q3	415577
1998Q1	309517	2003Q2	365803	2008Q3	406584	2013Q4	417265
1998Q2	311857	2003Q3	370428	2008Q4	397522	2014Q1	420091
1998Q3	314098	2003Q4	374127	2009Q1	390406	2014Q2	423249
1998Q4	317295	2004Q1	375324	2009Q2	389388	2014Q3	426022
1999Q1	318806	2004Q2	376455	2009Q3	390167	2014Q4	428347

3. Quarterly Australia Gross Domestic Product (AU GDP) Data for fifty five years

Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP
1960Q3	62699	1969Q1	93056	1977Q3	124632	1986Q1	160962
1960Q4	62391	1969Q2	94927	1977Q4	124221	1986Q2	160681
1961Q1	62420	1969Q3	96497	1978Q1	125099	1986Q3	161140
1961Q2	61661	1969Q4	98681	1978Q2	126118	1986Q4	163738
1961Q3	61314	1970Q1	100712	1978Q3	128077	1987Q1	165301
1961Q4	62081	1970Q2	102754	1978Q4	129122	1987Q2	168137
1962Q1	63864	1970Q3	102569	1979Q1	132635	1987Q3	171077
1962Q2	65094	1970Q4	103033	1979Q2	130506	1987Q4	174366
1962Q3	65610	1971Q1	104275	1979Q3	131781	1988Q1	175224
1962Q4	66768	1971Q2	104745	1979Q4	134307	1988Q2	175811
1963Q1	68278	1971Q3	108033	1980Q1	134898	1988Q3	177124
1963Q2	67373	1971Q4	107666	1980Q2	135231	1988Q4	179544
1963Q3	70159	1972Q1	106369	1980Q3	136029	1989Q1	181572
1963Q4	71638	1972Q2	108774	1980Q4	138348	1989Q2	185374
1964Q1	71569	1972Q3	108196	1981Q1	138871	1989Q3	186661
1964Q2	73362	1972Q4	109307	1981Q2	140977	1989Q4	186430
1964Q3	73820	1973Q1	112153	1981Q3	143892	1990Q1	187981
1964Q4	75876	1973Q2	112380	1981Q4	143269	1990Q2	188081
1965Q1	76488	1973Q3	113533	1982Q1	142109	1990Q3	187067
1965Q2	77689	1973Q4	116324	1982Q2	143358	1990Q4	188029
1965Q3	77511	1974Q1	116330	1982Q3	142456	1991Q1	185693
1965Q4	77662	1974Q2	113955	1982Q4	140178	1991Q2	185172
1966Q1	77415	1974Q3	115442	1983Q1	138772	1991Q3	185757
1966Q2	78474	1974Q4	115443	1983Q2	138449	1991Q4	186175
1966Q3	80749	1975Q1	115866	1983Q3	142754	1992Q1	187862
1966Q4	81234	1975Q2	119545	1983Q4	144818	1992Q2	189180
1967Q1	84393	1975Q3	118291	1984Q1	148331	1992Q3	190794
1967Q2	84272	1975Q4	116453	1984Q2	149866	1992Q4	194658
1967Q3	85912	1976Q1	121621	1984Q3	151245	1993Q1	196472
1967Q4	86611	1976Q2	122005	1984Q4	152282	1993Q2	197362
1968Q1	85818	1976Q3	123044	1985Q1	154754	1993Q3	197472
1968Q2	89147	1976Q4	124072	1985Q2	158237	1993Q4	201303
1968Q3	90328	1977Q1	123363	1985Q3	160243	1994Q1	204882
1968Q4	93674	1977Q2	125146	1985Q4	159842	1994Q2	207148

Quarterly Australia Gross Domestic Product (AU GDP) Data for fifty five years continued

Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP
1994Q3	209087	1999Q4	258749	2005Q1	305482	2010Q2	352372
1994Q4	210231	2000Q1	260643	2005Q2	307082	2010Q3	354131
1995Q1	210744	2000Q2	262675	2005Q3	310839	2010Q4	358039
1995Q2	212214	2000Q3	262854	2005Q4	313150	2011Q1	356698
1995Q3	215944	2000Q4	261697	2006Q1	313828	2011Q2	361486
1995Q4	217011	2001Q1	265039	2006Q2	314635	2011Q3	365720
1996Q1	221027	2001Q2	266972	2006Q3	317949	2011Q4	369377
1996Q2	221541	2001Q3	270001	2006Q4	322966	2012Q1	373199
1996Q3	224250	2001Q4	272834	2007Q1	327956	2012Q2	375378
1996Q4	225878	2002Q1	275108	2007Q2	330675	2012Q3	377463
1997Q1	226534	2002Q2	279434	2007Q3	333118	2012Q4	379566
1997Q2	233386	2002Q3	280491	2007Q4	335004	2013Q1	380471
1997Q3	233340	2002Q4	282770	2008Q1	339193	2013Q2	383444
1997Q4	236606	2003Q1	282866	2008Q2	340345	2013Q3	384740
1998Q1	239213	2003Q2	285042	2008Q3	342712	2013Q4	388070
1998Q2	241212	2003Q3	289448	2008Q4	339942	2014Q1	391553
1998Q3	245592	2003Q4	294214	2009Q1	343341	2014Q2	393991
1998Q4	249099	2004Q1	296426	2009Q2	345003	2014Q3	395491
1999Q1	251023	2004Q2	298099	2009Q3	346396	2014Q4	397658
1999Q2	252217	2004Q3	300683	2009Q4	348902	2015Q1	401153
1999Q3	254503	2004Q4	302837	2010Q1	350233	2015Q2	401816

4. Quarterly France Gross Domestic Product (France GDP) Data for fifty five years

Year/ Quarter	GDP	Year/ Quarter	GDP	Year/ Quarter	GDP	Year/ Quarter	GDP
1960Q3	114272	1969Q1	181172	1977Q3	258288	1986Q1	308498
1960Q4	115484	1969Q2	184946	1977Q4	260391	1986Q2	311999
1961Q1	117087	1969Q3	187464	1978Q1	263824	1986Q3	313604
1961Q2	117833	1969Q4	190293	1978Q2	266635	1986Q4	313910
1961Q3	118947	1970Q1	193239	1978Q3	268767	1987Q1	314745
1961Q4	121035	1970Q2	196425	1978Q4	271679	1987Q2	318759
1962Q1	123534	1970Q3	198435	1979Q1	274054	1987Q3	321141
1962Q2	125407	1970Q4	201057	1979Q2	275524	1987Q4	325800
1962Q3	127832	1971Q1	204266	1979Q3	279153	1988Q1	330048
1962Q4	129202	1971Q2	206415	1979Q4	279886	1988Q2	332798
1963Q1	128484	1971Q3	209240	1980Q1	282924	1988Q3	336774
1963Q2	133793	1971Q4	211233	1980Q2	280863	1988Q4	339979
1963Q3	138086	1972Q1	213576	1980Q3	281356	1989Q1	344994
1963Q4	138138	1972Q2	215401	1980Q4	280938	1989Q2	348237
1964Q1	141087	1972Q3	218493	1981Q1	281911	1989Q3	351547
1964Q2	142709	1972Q4	221923	1981Q2	283496	1989Q4	354986
1964Q3	144026	1973Q1	225800	1981Q3	285546	1990Q1	358597
1964Q4	146064	1973Q2	229431	1981Q4	287243	1990Q2	359991
1965Q1	146929	1973Q3	233036	1982Q1	289498	1990Q3	361148
1965Q2	149422	1973Q4	235602	1982Q2	291545	1990Q4	360888
1965Q3	151584	1974Q1	239572	1982Q3	291900	1991Q1	360956
1965Q4	153851	1974Q2	241254	1982Q4	293485	1991Q2	363503
1966Q1	155281	1974Q3	243506	1983Q1	294469	1991Q3	364800
1966Q2	157638	1974Q4	239287	1983Q2	294824	1991Q4	366789
1966Q3	159611	1975Q1	237727	1983Q3	295123	1992Q1	369983
1966Q4	160759	1975Q2	237076	1983Q4	296693	1992Q2	369878
1967Q1	163358	1975Q3	237162	1984Q1	298517	1992Q3	369322
1967Q2	165188	1975Q4	242059	1984Q2	299362	1992Q4	368319
1967Q3	167210	1976Q1	244436	1984Q3	301262	1993Q1	366004
1967Q4	168891	1976Q2	247810	1984Q4	301260	1993Q2	366572
1968Q1	173102	1976Q3	250549	1985Q1	302019	1993Q3	367791
1968Q2	164395	1976Q4	252236	1985Q2	304422	1993Q4	368427
1968Q3	177107	1977Q1	255139	1985Q3	306359	1994Q1	370297
1968Q4	179393	1977Q2	255962	1985Q4	307560	1994Q2	374699

Quarterly France Gross Domestic Product (France GDP) Data for fifty five years continued

Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP	Year/ Quarterly	GDP
1994Q3	377229	1999Q4	433082	2005Q1	477175	2010Q2	497884
1994Q4	380473	2000Q1	438491	2005Q2	478415	2010Q3	500788
1995Q1	382227	2000Q2	441746	2005Q3	480972	2010Q4	503409
1995Q2	384168	2000Q3	444561	2005Q4	484669	2011Q1	509219
1995Q3	384439	2000Q4	448322	2006Q1	487849	2011Q2	508803
1995Q4	385122	2001Q1	451268	2006Q2	492945	2011Q3	509799
1996Q1	387505	2001Q2	451408	2006Q3	492913	2011Q4	511046
1996Q2	388449	2001Q3	452756	2006Q4	496738	2012Q1	511258
1996Q3	390330	2001Q4	451864	2007Q1	500164	2012Q2	509776
1996Q4	390729	2002Q1	454400	2007Q2	503460	2012Q3	511124
1997Q1	392332	2002Q2	457117	2007Q3	505475	2012Q4	511075
1997Q2	396680	2002Q3	458387	2007Q4	506852	2013Q1	511761
1997Q3	399759	2002Q4	457818	2008Q1	509256	2013Q2	515619
1997Q4	403777	2003Q1	458113	2008Q2	506482	2013Q3	515016
1998Q1	406967	2003Q2	457916	2008Q3	505031	2013Q4	516114
1998Q2	411283	2003Q3	461191	2008Q4	497016	2014Q1	515222
1998Q3	414149	2003Q4	465244	2009Q1	489186	2014Q2	514610
1998Q4	417290	2004Q1	468149	2009Q2	488813	2014Q3	515823
1999Q1	419674	2004Q2	471646	2009Q3	489482	2014Q4	516402
1999Q2	423406	2004Q3	473663	2009Q4	492688	2015Q1	519856
1999Q3	428117	2004Q4	476863	2010Q1	494954	2015Q2	519796

Appendix B

Intra-class correlation coefficient and Levene's Test Real Data

1. Intra-class correlation coefficient for USGDP

		95% Confidence Interval		F Test with True Value			
	Intraclass Correlation[a]	Lower Bound	Upper Bound	Value	df1	df2	Sig
Single Measures	.01[b]	-.12	.14	1.02	22	22	.44
Average Measures	.02[c]	-.28	.25	1.02	22	22	.44

A two-way mixed effects model where people effects are random and measures effects are fixed.

A Type C intra-class correlation coefficients using a consistent definition-the between-measure variance are excluded from the denominator variance.

b. The estimator is the same, whether the interaction effect is present or not.
c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Levene's Test for Equal Variances Independent Samples Test for US GDP

Independent samples test									
	Levene's Test for Equality of Variances ……………		t-test for Equality of Means …………………………………………………………………						
								95% Confidence Interval of the Difference ………………..	
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Equal variances assumed	1.414	0.235	2.159	438	0.031	0.059	0.027	0.005	0.113
Equal variances not assumed			2.159	255.24	0.032	0.059	0.027	0.005	0.113

2. Intra-class correlation coefficient for UK GDP

	Intraclass Correlation[a]	95% Confidence Interval Lower Bound	Upper Bound	F Test with True Value Value	df1	df2	Sig
Single Measures	-.014[b]	-.146	.118	.972	219	219	.583
Average Measures	-.029	-.341	.211	.972	219	219	.583

A two-way mixed effects model where people effects are random and measures effects are fixed.

a. Type C intra-class correlation coefficients using a consistent definition-the between-measure variances are excluded from the denominator variance.
b. The estimator is the same, whether the interaction effect is present or not.
c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Levene's test for equal variances Independent Samples Test for UK GDP

Independent samples test									
	Levene's Test for Equality of Variances		t-test for Equality of Means					95% Confidence Interval of the Difference	
	F	Sig.	t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	Lower	Upper
Equal variances assumed	5.504	.019	1.133	438	.258	.015	.014	-.011	.042
Equal variances not assumed			1.133	255.50	.258	.015	.014	-.011	.042

3. Intra-class correlation coefficient for AU GDP

	Intraclass Correlation[a]	95% Confidence Interval Lower Bound	Upper Bound	F Test with True Value Value	df1	df2	Sig
Single Measures	.020[b]	-.112	.152	1.042	219	219	.381
Average Measures	.040[c]	-.252	.264	1.042	219	219	.381

A two-way mixed effects model where people effects are random and measures effects are fixed.

a. Type C intra-class correlation coefficients using a consistent definition-the between-measure variance are excluded from the denominator variance.

b. The estimator is the same, whether the interaction effect is present or not.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Levene's test for equal variances Independent Samples Test for AU GDP

	Levene's Test for Equality of Variances: F	Sig.	t-test for Equality of Means: t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference: Lower	Upper
Equal variances assumed	.045	.833	-2.994	438	.003	-.014	.005	-.023	-.005
Equal variances not assumed			-2.994	424.76	.003	-.014	.005	-.023	-.005

4. Intra-class correlation coefficient for France GDP

	Intraclass Correlation[a]	95% Confidence Interval Lower Bound	Upper Bound	F Test with True Value Value	df1	df2	Sig
Single Measures	.016[b]	-.116	.148	1.033	219	219	.405
Average Measures	.032[c]	-.262	.258	1.033	219	219	.405

A two-way mixed effects model where people effects are random and measures effects are fixed.

a. Type C intra-class correlation coefficients using a consistent definition-the between-measure variance are excluded from the denominator variance.

b. The estimator is the same, whether the interaction effect is present or not.

c. This estimate is computed assuming the interaction effect is absent, because it is not estimable otherwise.

Levene's test for equal variances Independent Samples Test for France GDP

Independent samples test

	Levene's Test for Equality of Variances F	Sig.	t-test for Equality of Means t	df	Sig. (2-tailed)	Mean Difference	Std. Error Difference	95% Confidence Interval of the Difference Lower	Upper
Equal variances assumed	.271	.603	2.684	438	.008	.020	.008	.005	.035
Equal variances not assumed			2.684	373.49	.008	.020	.008	.005	.035

Appendix C

The Log-likelihood

1. The Log-Likelihood Values for 200 Sample size of Low Leverage and different Values of Skewness

Low leverage and low skewness for 40 equal variances

-1480.69	-1476.68	-1454.77	-1341.02	-1458.05	-1448.52
-1360.76	-1347.23	-1336.74	-1362.25	-1407.78	-1433.82
-1374.86	-1318.28	-1383.83	-1437.41	-1397.73	-1430.27
-1396.86	-1361.00	-1362.71	-1327.10	-1394.40	-1440.67
-1381.62	-1334.76	-1432.11	-1429.17	-1392.74	-1413.88
-1368.69	-1278.90	-1389.05	-315.431	-1433.04	-1403.91
-1300.23	-1417.90	-1374.60	-1323.74		

Low leverage and moderate skewness for 44 equal variances

-1408.88	-1412.84	-1417.85	-1305.38	-1361.89	-1402.64
-1400.01	-1325.60	-1378.95	-1442.18	-1279.72	-1433.54
-1406.93	-1429.50	-1348.56	-1353.01	-1323.97	-1331.18
-1304.29	-1386.27	-1367.69	-1381.06	-1331.04	-1371.04
-1352.89	-1404.61	-1392.78	-1411.30	-1367.00	-1336.88
-1321.96	-1361.73	-1357.76	-326.07	-1334.46	-1278.75
-1429.75	-1335.85	-1210.69	-1393.98	-1378.41	-1404.55
-1462.58	-1394.88				

Low leverage and high skewness for 43 equal variances

-1408.88	-1408.88	-1417.85	-1305.38	-1361.89	-1402.64
-1400.01	-1325.60	-1378.95	-1442.18	-1279.72	-1433.54
-1406.93	-1429.50	-1348.56	-1353.01	-1323.97	-1331.18
-1304.29	-1386.27	-1367.69	-1381.06	-1331.04	-1371.04
-1411.21	-1366.90	-1336.03	-1322.11	-1359.97	-1357.66
-1443.71	-1333.36	-1278.70	-317.01	-1335.13	-1208.27
-1394.36	-1379.15	-1404.40	-1462.98	-1395.24	-1439.32
-1402.98					

2. The Log-Likelihood Values for 200 Sample size of Moderate Leverage and different Values of Skewness

Moderate leverage and low skewness for 40 equal variances					
-1321.80	-1328.98	-1433.48	-1345.96	-1356.46	-2172.37
-1422.38	-1396.74	-1428.70	-1343.75	-1389.54	-1286.90
-1329.06	-1384.08	-1368.80	-1405.64	-1360.08	-1456.30
-1401.54	-1275.89	-1294.41	-1426.36	-1383.56	-1421.46
-1313.38	-1323.85	-1423.28	-1376.72	-1455.41	-1384.32
-1335.79	-1383.15	-1365.69	-303.93	-1408.91	-1352.43
-1307.73	-1375.32	-1361.76	-1496.46		
Moderate leverage and moderate skewness for 45 equal variances					
-1430.34	-1631.54	2817.20	-1408.94	-1402.86	-1365.49
-1437.46	-1395.26	-1403.64	-1442.39	-1323.14	-1432.56
-1387.93	-1366.33	-1368.59	-1395.98	-1416.47	-1273.47
-1394.08	-1333.64	-1394.20	-1384.32	-1366.24	-1412.68
-1336.02	-1339.85	-1370.12	-1332.26	-1332.99	-1350.02
-1337.44	-1391.55	-1393.67	-307.17	-1326.93	-1282.96
-1338.00	-1392.69	-1283.39	-1336.35	-1416.69	-1359.39
-1380.94	-1342.92	-1361.48			
Moderate leverage and high skewness for 41 equal variances					
-1350.24	-1353.32	-1358.54	-1368.06	-1293.26	-1339.24
-1324.88	-1437.11	-1410.32	-1365.82	-1354.34	-1412.71
-1337.87	-1429.30	-1363.61	-1375.96	-1370.92	-1372.37
-1358.24	-1393.90	-1304.10	-1393.50	-1401.12	-1409.85
-1396.00	-1458.76	-1350.42	-1450.58	-1421.99	-1375.44
-1401.42	-1290.98	-1405.77	-304.96	-1274.79	-1329.78
-1324.23	-1390.19	-1448.74	-1355.07	-1393.68	

3. The Log-Likelihood Values for200 Sample size of High Leverage and different Values of Skewness

High leverage and low skewness for 41 equal variances					
-1408.88	-1412.48	-1417.85	-1305.38	-1361.89	-1402.64
-1400.01	-1325.60	-1378.95	-1442.18	-1279.72	-1433.54
-1406.93	-1429.50	-1348.56	-1353.01	-1323.97	-1331.18
-1304.29	-1386.27	-1367.69	-1381.06	-1331.04	-1371.04
-1352.89	-1404.61	-1392.78	-1411.30	-1367.00	-1336.88
-1321.96	-1361.73	-1357.76	-326.07	-1334.46	-1278.75
-1429.75	-1335.85	-1210.69	-1393.98	-1378.41	
High leverage and moderate skewness for 44 equal variances					
-1408.876	-1402.668	-1396.69	-1403.38	-1399.27	-1325.87
-1377.588	-1441.646	-1279.49	-1434.55	-1406.82	-1428.66
-1349.202	-1353.458	-1323.84	-1330.25	-1303.92	-1386.74
-1368.038	-1381.240	-1331.04	-1371.68	-1352.92	-1405.82
-1393.210	-1411.105	-1366.66	-1336.61	-1322.01	-1361.76
-1357.083	-1444.048	-1334.38	-286.13	-1429.24	-1335.51
-1211.513	-1393.551	-1379.15	-1404.97	-1462.81	-1394.86
-1439.359	-1402.866				
High leverage and high skewness for 43 equal variances					
-1385.99	-1387.98	-1396.69	-1403.38	-1399.27	-1325.87
-1377.59	-1441.65	-1279.49	-1434.55	-1406.82	-1428.66
-1349.20	-1353.46	-1323.84	-1330.25	-1303.92	-1386.74
-1368.04	-1381.24	-1331.04	-1371.68	-1352.92	-1405.82
-1393.21	-1411.11	-1366.66	-1336.61	-1322.01	-1361.76
-1357.08	-1444.05	-286.13	-1334.38	-1429.24	-1335.51
-1211.51	-1393.55	-1379.15	-1404.97	-1462.81	-1394.86
-1439.36					

4. The Log-Likelihood Values for 250 Sample size of Low Leverage and different Values of Skewness

Low leverage and low skewness for 45 equal variances					
-1476.42	-1462.35	1449.84	-1342.84	-1425.49	-1404.73
-1370.48	-1444.24	-1347.29	-1405.56	-1375.90	-1445.99
-1369.85	-1347.22	-1443.71	-1393.35	-1364.73	-1415.22
-1324.51	-1407.95	-1330.58	-1346.45	-1372.82	-1386.91
-1473.02	-1386.46	-1390.39	-1345.02	-1382.86	-1397.24
-1308.67	-1376.17	-1417.94	-1417.94	-1405.89	-1325.59
-1431.57	-1391.72	-1422.62	-1369.12	-1436.26	-1344.94
-1398.69	-1371.16	-1357.20			
Low leverage and moderate skewness for 48 equal variances					
-1407.61	-1407.61	-1335.67	-1337.59	-1378.93	-1378.93
-1351.28	-1366.68	-1375.19	-1453.98	-1390.95	-1331.27
-1405.29	-1347.73	-1405.82	-1343.84	-1402.93	-1320.52
-1370.74	-1300.55	-1294.20	-1354.28	-1361.77	-1398.92
-1390.28	-1402.72	-1297.32	-1370.12	-1343.01	-1409.22
-1409.10	-1388.73	-1360.61	-1380.25	-1386.09	-1372.22
-1367.02	-1451.00	-1407.49	-1411.59	-1444.01	-1453.08
-1430.76	-1447.09	-1331.38	-1377.92	-1388.95	-1383.34
Low leverage and high skewness for 46 equal variances					
-1344.60	-1341.42	-1357.34	-1370.40	-1383.75	-1415.46
-1456.02	-1467.32	-1365.12	-1439.89	-1369.30	-1389.48
-1368.49	-1410.85	-1358.19	-1390.97	-1348.24	-1367.83
-1343.96	-1333.13	-1441.47	-1432.94	-1356.90	-1334.62
-1363.72	-1372.48	-1414.15	-1335.40	-1369.83	-1398.17
-1315.44	-1388.40	-1316.32	-1412.34	-1420.00	-1442.26
-1347.41	-1397.39	-1448.18	-1362.22	-1476.07	-1396.27
-1408.75	-1343.07	-1427.53	-1403.37		

5. The Log-Likelihood Values for 250 Sample size of Moderate Leverage and different Values of Skewness

Moderate leverage and low skewness for 43 equal variances					
-1344.60	-1454.77	-1357.34	-1370.40	-1383.75	-1415.46
-1456.02	-1467.32	-1365.12	-1439.89	-1369.30	-1389.48
-1368.49	-1410.85	-1358.19	-1390.97	-1348.24	-1367.83
-1343.96	-1333.13	-1441.47	-1432.94	-1356.90	-1334.62
-1363.72	-1372.48	-1414.15	-1335.40	-1369.83	-1398.17
-1315.44	-1388.40	-1345.30	-1316.32	-1420.00	-1442.26
-1347.41	-1397.39	-1448.18	-1362.22	-1476.07	-1396.27
-1408.75					
Moderate leverage and moderate skewness for 44 equal variances					
-1344.60	-1362.64	-1357.34	-1370.40	-1383.75	-1415.46
-1456.02	-1467.32	-1365.12	-1439.89	-1369.30	-1389.48
-1368.49	-1410.85	-1358.19	-1390.97	-1348.24	-1367.83
-1343.96	-1333.13	-1441.47	-1432.94	-1356.90	-1334.62
-1363.72	-1372.48	-1414.15	-1335.40	-1369.83	-1398.17
-1315.44	-1388.40	-1316.32	-1343.45	-1420.00	-1442.26
-1347.41	-1397.39	-1448.18	-1362.22	-1476.07	-1396.27
-1408.75	-1343.07				
Moderate leverage and high skewness for 47 equal variances					
-1427.49	-1412.44	-1402.22	-1444.17	-1347.17	-1406.17
-1376.46	-1446.62	-1370.01	-1347.84	-1444.47	-1393.43
-1364.33	-1415.83	-1325.51	-1407.05	-1330.57	-1345.81
-1372.90	-1388.71	-1474.44	-1387.07	-1390.94	-1345.32
-1382.90	-1396.40	-1308.09	-1376.15	-1417.32	-1312.86
-1407.16	-1326.70	-1431.08	-1315.43	-1422.65	-1369.19
-1436.45	-1344.93	-1399.09	-1368.21	-1357.47	-1407.62
-1362.91	-1306.98	-1336.63	-1294.68	-1377.99	

6. The Log-Likelihood Values for250 Sample size of High Leverage and different Values of Skewness

High leverage and low skewness for 45 equal variances					
-1344.60	-1376.12	-1403.83	-1320.06	-1370.01	-1381.98
-1414.84	-1457.44	-1467.61	-1365.63	-1439.53	-1369.84
-1389.64	-1368.31	-1411.06	-1353.17	-1391.26	-1348.86
-1368.90	-1343.72	-1332.86	-1441.77	-1434.17	-1357.19
-1336.29	-1363.71	-1370.32	-1414.27	-1335.40	-1370.57
-1398.01	-1315.59	-1389.22	-1428.42	-1315.64	-1387.49
-1420.34	-1441.32	-1348.31	-1397.39	-1448.25	-1362.21
-1476.26	-1408.75	-1343.24			
High leverage and moderate skewness for 45 equal variances					
-1427.49	-1454.77	-1439.62	-1370.89	-1443.11	-1347.00
-1406.16	-1376.50	-1446.76	-1370.04	-1347.84	-1443.65
-1392.93	-1364.83	-1415.83	-1324.39	-1408.00	-1330.34
-1346.67	-1372.88	-1387.12	-1474.32	-1385.94	-1390.88
-1344.99	-1382.90	-1397.95	-1308.87	-1376.06	-1417.60
-1313.34	-1407.43	-1391.68	-1381.62	-1368.67	-1436.86
-1344.37	-1399.69	-1371.16	-1357.69	-1407.73	-1362.94
-1306.79	-1337.25	-1294.48			
High leverage and high skewness for 47 equal variances					
-1379.13	-1480.69	-1394.25	-1375.10	-1331.24	-1404.70
-1347.66	-1406.57	-1343.14	-1401.56	-1320.40	-1371.05
2618.47	-1294.89	-1354.46	-1362.15	-1398.84	-1391.12
-1402.92	-1298.17	-1373.02	-1342.79	-1408.54	-1408.92
-1390.65	-1361.80	-1444.40	-1305.33	-1379.34	-1441.76
-1381.61	-1386.65	-1372.51	-1360.76	-1450.87	-1408.22
-1412.28	-1453.44	-1365.96	-1445.84	-1430.44	-1447.20
-1331.22	-1379.46	-1389.03	-1383.19	-1373.61	

7. The Log-Likelihood Values for 300 Sample size of Low Leverage and different Values of Skewness

Low leverage and low skewness for 47 equal variances					
-1449.13	-1399.32	-1394.84	-1317.98	-1420.62	-1403.50
-1415.72	-1390.95	-1282.88	-1382.19	-1364.68	-1433.95
-1399.91	-1427.60	-1335.89	-1374.00	-1366.63	-1375.77
-1400.46	-1419.56	-1417.26	-1431.12	-1404.96	-1373.84
-1380.23	-1425.37	-1375.77	-1332.12	-1418.60	-1362.49
-1409.64	-1439.96	-1376.34	-1371.56	-1364.44	-1436.93
-1384.66	-1373.25	-1346.16	-1364.31	-1280.63	-1343.02
-1372.25	-1500.61	-1373.78	-1382.99	-1360.86	
Low leverage and moderate skewness for 50 equal variances					
-1306.99	-1353.52	-1378.54	-1327.48	-1408.10	-1392.01
-1416.21	-1378.69	-1288.34	-1357.94	-1326.05	-1295.02
-1438.07	-1389.06	-1401.19	-1380.88	-1379.24	-1328.29
-1416.33	-1340.48	-1374.88	-1390.38	-1440.00	-1325.27
-1346.95	-1346.95	-1370.90	-1356.91	-1385.36	-1369.31
-1350.87	-1335.04	-1462.98	-1422.27	-1327.27	-1366.74
-1431.89	-1418.18	-1419.37	-1352.77	-1422.06	-1383.04
-1351.20	-1395.04	-1374.63	-1315.81	-1334.19	-1348.69
-1316.41	-1404.21				
Low leverage and high skewness for 47 equal variances					
-1401.78	-1404.26	-1409.82	-1392.05	-1431.27	-1336.96
-1390.71	-1391.46	-1396.57	-1340.16	-1403.45	-1328.80
-1329.79	-1454.00	-1489.80	-1324.30	-1371.81	-1325.84
-1329.59	-1309.90	-1403.35	-1374.27	-1441.11	-1452.95
-1307.99	-1401.02	-1439.82	-1358.96	-1395.44	-1378.61
-1393.29	-1341.44	-1368.14	-1345.74	-1300.91	-1417.67
-1395.25	-1332.23	-1459.85	-1365.93	-1422.39	-1357.87
-1399.57	-1424.61	-1449.96	-1413.98	-1370.72	

8. The Log-Likelihood Values for 300 Sample size of Moderate Leverage and different Values of Skewness

Moderate leverage and low skewness 48 for equal variances					
-1401.78	-1406.23	-1409.82	-1392.05	-1431.27	-1336.96
-1390.71	-1391.46	-1396.57	-1340.16	-1403.45	-1328.80
-1329.79	-1454.00	-1489.80	-1324.30	-1371.81	-1325.84
-1329.59	-1309.90	-1403.35	-1374.27	-1441.11	-1452.95
-1307.99	-1401.02	-1358.52	-1395.53	-1378.65	-1393.76
-1341.92	-1365.62	-1300.98	-1325.73	1397.76	-1332.23
-1460.17	-1365.99	-1423.36	-1357.83	-1399.86	-1421.59
-1449.67	-1413.92	-1370.40	-1372.82	-1355.10	-1314.33

Moderate leverage and moderate skewness for 51 equal variances					
-1359.06	-410.37	-421.69	-407.53	-422.06	-460.75
-428.60	-443.11	-415.40	-430.32	-416.07	-423.06
-427.00	-426.03	-431.54	-417.84	-419.94	-422.36
-424.51	-398.89	-412.60	-421.19	-426.36	-443.51
-423.21	-422.15	-417.75	-407.21	-448.65	-428.87
-437.08	-413.84	-429.38	-433.78	-425.49	-407.68
-423.95	-422.39	-422.26	-432.18	-401.32	-441.32
-420.62	-440.28	-433.93	-428.04	-442.41	-433.20
-414.68	-442.46	-428.46			

Moderate leverage and high skewness for 47 equal variances					
-416.20	-437.85	-438.52	-417.78	-423.85	-429.66
-426.76	-416.77	-655.41	-415.49	-417.71	-420.56
-427.05	-668.16	-424.57	-416.73	-435.10	-416.52
-426.10	-436.33	-402.39	-415.68	-421.58	-439.07
-427.29	-421.25	-417.80	-393.54	-410.72	-431.46
-414.86	-428.28	-429.11	-416.25	-438.87	-399.22
-434.10	-407.85	-429.15	-437.20	-420.03	-426.93
-432.78	-442.17	-421.82	-428.92	-427.69	

9. The Log-Likelihood Values for 300 Sample size of High Leverage and different Values of Skewness

High leverage and low skewness for 40 equal variances					
-426.76	-414.65	-418.47	-415.49	-417.71	-420.56
-427.05	-416.91	-442.57	-396.44	-426.49	-443.74
-399.74	-404.00	-452.18	-439.41	-435.16	-435.99
-417.41	-434.47	-436.70	-433.33	-450.40	-444.39
-425.41	-443.59	-406.79	-413.50	-416.52	-415.65
-417.24	-405.84	406.96	424.24	-431.31	-451.18
-442.24	-427.99	-417.23	-426.51		
High leverage and moderate skewness for 48 equal variances					
-425.16	-434.30	-398.94	-437.01	-428.13	-449.72
-418.42	-419.69	-418.81	-434.81	-426.88	-447.61
-422.00	-440.23	-398.68	-450.71	-410.75	-420.49
-434.14	-422.02	-423.96	-434.07	-418.28	-399.58
-433.49	-402.81	-419.39	-420.25	-425.14	-419.55
-436.41	-416.14	-390.02	-421.14	-431.79	-422.74
-400.69	-431.13	-421.66	-431.29	-430.91	-421.57
-429.60	-403.06	-441.50	-420.79	-425.11	-421.01
High leverage and high skewness for 48 equal variances					
-437.37	-425.88	-435.10	-416.63	-442.75	-424.32
-408.40	-416.70	-423.93	-444.38	-441.90	-408.01
-433.50	-410.75	-409.97	-415.31	-422.31	-424.49
-422.95	-421.61	-436.30	-438.30	-418.37	-421.34
-434.46	-420.30	-417.30	-424.44	-440.11	-420.00
-408.21	-430.97	-422.50	-440.60	-434.92	-407.27
-425.67	-417.38	-408.68	-405.74	-432.78	-423.69
-424.52	-418.99	-415.39	-393.91	-433.12	-430.97

Appendix D

Bayesian Model Averaging (BMA) Simulation Output

1. Low Leverage and Low Skewness of 200 Sample Size

Predictor	**p!=0**	**EV**	**SD**	**model 1**	**Model 2**	**model 3**	**model 4**	**model 5**
Intercept	100	7.19E-03	0.007	0.007	0.0081	0.0076	0.0075	0.0074
X1	2.1	3.68E-05	0.0036	.	.		.	.
x2	2.1	4.19E-05	0.0041	.	.		.	.
X3	2.1	4.57E-05	0.0044	.	.		.	.
X4	2.1	4.71E-05	0.0046	.	.		.	.
X5	2.1	5.39E-05	0.0052	.	.		.	.
X6	2.1	6.33E-05	0.0043	.	.		.	.
X7	2.1	6.56E-05	0.0063	.	.		.	.
X8	2.1	7.23E-05	0.0049	.	.	.		.
x9	2.2	8.06E-05	0.0045	.	.		.	.
X10	2.1	9.49E-05	0.0065	.	.	.	.	.
X11	2.1	1.01E-04	0.0069	.	.	.	.	.
X12	2.1	1.09E-04	0.0074	.	.	.	.	.
X13	2.2	1.21E-04	0.0047	.	.	.	.	.
X14	2.2	1.30E-04	0.0056	.	.	.	.	.
X15	2.2	1.39E-04	0.0078	.	.	.	.	.
X16	2.1	1.52E-04	0.0104	.	.	.	.	.
X17	2.2	1.71E-04	0.0083	.	.	.	.	.
X28	2.2	-5.39E-04	0.0163	.	.	.	.	-0.0246
X29	2.2	-3.98E-04	0.0135	.	.	.	.	.
X30	2.2	-3.37E-04	0.0083	.	.	-0.0151	.	.
X31	2.2	-2.65E-04	0.0090	.	.	.		.
X32	2.2	-2.29E-04	0.0073	.	.		.	.
X33	2.2	-2.07E-04	0.0055	.	.	.	0.9358	.
x34	2.2	-1.73E-04	0.0074	.	.		.	.
X35	2.2	-1.62E-04	0.0049	.	.	.	.	.
X36	2.2	-1.43E-04	0.0056	.	.	.	.	.
X37	2.1	-1.26E-04	0.0122	.	.	.	.	.
X38	2.2	-1.20E-04	0.0052	.	.	.	.	.
X40	2.1	-9.43E-05	0.0091	.	.	.	.	.
nVar				0	0	1	1	1
r2				0	0.012	0	0	0
BIC				0	2.9141	5.2163	5.228	5.2463
post prob				0.302	0.07	0.031	0.022	0.022

2. .Low Leverage and Moderate Skewness of 200 Sample Size

Predictor	**p!=0**	**EV**	**SD**	**model 1**	**model 2**	**model 3**	**Model 4**	**model 5**
Intercept	100	9.86E-03	0.0096	0.0095	0.0114	0.0102	0.0101	0.0099
X1	2	4.41E-05	0.0044	.	.	.	.	.
x2	2	5.27E-05	0.0053	.	.	.	.	.
X3	2	5.74E-05	0.0058	.	.	.	.	.
X4	2	6.11E-05	0.0062	.	.	.	.	.
X5	2	7.02E-05	0.0071	.	.	.	.	.
X6	2	7.58E-05	0.0076	.	.	.	.	.
X7	2	7.90E-05	0.0079	.	.	.	.	.
X8	2	8.24E-05	0.0083	.	.	.	.	.
x9	2	9.03E-05	0.0091	.	.	.	.	.
X10	2	9.54E-05	0.0068	.	.	.	.	.
X11	2	1.05E-04	0.0106	.	.	.	.	.
X12	2	1.12E-04	0.0080	.	.	.	.	.
X13	2	1.20E-04	0.0070	.	.	.	.	.
X14	2	1.27E-04	0.0090	.	.	.	.	.
X15	2	1.43E-04	0.0050	.	.	.	.	0.0071
X17	2	1.75E-04	0.0101	.	.	.	.	.
X31	2	-5.12E-04	0.0153	.	.	.	-0.0251	.
X32	2	-4.17E-04	0.0114	.	.	-0.0203		.
X33	2	-3.31E-04	0.0125	.	.	.	.	.
x34	2	-2.75E-04	0.0159	.	.	.	.	.
X35	2	-2.48E-04	0.0094	.	.	.	.	.
X36	2	-2.17E-04	0.0097	.	.	.	.	.
X37	2	-1.95E-04	0.0087	.	.	.	.	.
X38	2	-1.75E-04	0.0101	.	.	.	.	.
X39	2	-1.65E-04	0.0062	.	.	.	.	.
X40	2	-1.48E-04	0.0086	.	.	.	.	.
X41	2	-1.35E-04	0.0136	.	.	.	.	.
X42	2	-1.26E-04	0.0127	.	.	.	.	.
X44	2	-9.48E-05	0.0095	.	.	.	.	.
nVar				0	0	1	1	1
r2				0	0.019	0	0	0
BIC				0	1.372	5.2283	5.2403	5.2563
post prob				0.28	0.141	0.02	0.02	0.02

3. .Low Leverage and High Skewness of 200 Sample Size

Predictor	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100	0.0173	0.0172	0.017	0.0182	0.0181	0.0181	0.0179
X5	2.3	0.0002	0.0133	.	.	.	.	.
X6	2.3	0.0003	0.0123	.	.	.	.	.
X7	2.3	0.0003	0.0142	.	.	.	.	.
X8	2.3	0.0003	0.0215	.	.	.	.	.
x9	2.3	0.0004	0.0168	.	.	.	.	.
X10	2.3	0.0004	0.0258	.	.	.	.	.
X11	2.3	0.0004	0.0170	.	.	.	.	.
X12	2.3	0.0005	0.0152	.	.	.	.	0.0224
X13	2.3	0.0006	0.0161	.	.	0.0258	.	.
X14	2.3	0.0007	0.0238	.	.	.	.	.
X15	2.3	0.0008	0.0517	.	.	.	.	.
X16	2.3	0.0010	0.0336	.	.	.	.	.
X17	2.3	0.0014	0.0375	.	.	.	0.0603	.
X18	2.3	0.0021	0.0544	.	0.0909	.	.	.
x19	2.3	0.0041	0.1342	.	.	.	.	.
X20	2.3	-0.0041	0.1274	.	.	.	.	.
x21	2.3	-0.0020	0.0713	.	.	.	.	.
x22	2.3	-0.0013	0.0617	.	.	.	.	.
X23	2.3	-0.0010	0.0416	.	.	.	.	.
X24	2.3	-0.0008	0.0306	.	.	.	.	.
X25	2.3	-0.0007	0.0238	.	.	.	.	.
X26	2.3	-0.0006	0.0264	.	.	.	.	.
X27	2.3	-0.0005	0.0231	.	.	.	.	.
X28	2.3	-0.0004	0.0185	.	.	.	.	.
X29	2.3	-0.0004	0.0153	.	.	.	.	.
X30	2.3	-0.0004	0.0168	.	.	.	.	.
X31	2.3	-0.0003	0.0128	.	.	.	.	.
X32	2.3	-0.0003	0.0142	.	.	.	.	.
x34	2.3	-0.0003	0.0172	.	.	.	.	.
X38	2.3	-0.0002	0.0136	.	.	.	.	.
nVar				0	1	1	1	1
r2				0	0	0	0	0
BIC				0	5.2283	5.2343	5.2343	5.2463
post prob				0.317	0.023	0.023	0.023	0.023

4. .Moderate Leverage and Low Skewness of 200 Sample Size

Predictor	**p!=0**	**EV**	**SD**	**model 1**	**model 2**	**model 3**	**model 4**	**model 5**
Intercept	100	1.63E-02	0.0114	0.0160	0.0172	0.0170	0.0170	0.0169
X1	2.2	8.74E-05	0.0059	.	.	.	.	
X5	2.2	1.28E-04	0.0086	.	.	.	.	
X6	2.3	1.59E-04	0.0062	.	.	.	.	
X7	2.2	1.81E-04	0.0086	.	.	.	.	
X10	2.2	2.26E-04	0.0107	.	.	.	.	
X11	2.2	2.41E-04	0.0115	.	.	.	.	
X12	2.3	2.64E-04	0.0089	.	.	.	.	
X13	2.3	2.85E-04	0.0095	.	.	.	.	
X14	2.3	3.18E-04	0.0081	.	.	.	.	
X16	2.3	3.66E-04	0.0142	.	.	.	.	
X17	2.3	4.06E-04	0.0157	.	.	.	.	
x19	2.3	5.39E-04	0.0148	.	.	.	.	
X20	2.3	6.10E-04	0.0236	.	.	.	.	
x21	2.2	7.17E-04	0.0481	.	.	.	.	
x22	2.3	9.64E-04	0.0228	.	.	.	.	
X23	2.4	1.34E-03	0.0259	.	.	0.0567	.	
X24	2.3	1.97E-03	0.0417	.	.	.	.	
X25	2.3	3.70E-03	0.1240	.	.	.	.	
X26	2.3	-3.74E-03	0.1120	.	.	.	.	
X27	2.3	-1.87E-03	0.0560	.	.	.	.	-0.0564
X28	2.4	-1.33E-03	0.0268	.	.	.	.	
X29	2.3	-9.75E-04	0.0217	.	.	.	.	
X30	2.4	-8.24E-04	0.0147	.	-0.0344	.	.	
X31	2.3	-6.36E-04	0.0161	.	.	.	.	
X32	2.3	-5.63E-04	0.0119	.	.	.	.	
X33	2.4	-5.03E-04	0.0097	.	.	.	-0.0213	
x34	2.3	-4.33E-04	0.0097	.	.	.	.	
X35	2.3	-3.77E-04	0.0103	.	.	.	.	
X36	2.3	-3.54E-04	0.0079	.	.	.	.	
X37	2.2	-3.02E-04	0.0143	.	.	.	.	
nVar				o	1	1	1	1
r2				0	0.001	0.001	0.001	0.001
BIC				0	5.1463	5.1703	5.1703	5.1703
post prob				0.314	0.024	0.024	0.024	0.02

5. Moderate Leverage and Moderate Skewness of 200 Sample Size

Predictor	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100	9.19E-03	0.0091	0.0090	0.0096	0.0096	0.0095	0.0095
X7	2.3	8.91E-05	0.0059	.	.	.	.	.
X12	2.3	1.29E-04	0.0070	.	.	.	.	.
X13	2.3	1.39E-04	0.0065	.	.	.	.	.
X14	2.3	1.50E-04	0.0063	.	.	.	.	.
X15	2.3	1.58E-04	0.0105	.	.	.	.	.
X16	2.3	1.71E-04	0.0114	.	.	.	.	.
X17	2.3	1.88E-04	0.0102	.	.	.	.	.
X18	2.3	2.07E-04	0.0112	.	.	.	.	.
x19	2.3	2.30E-04	0.0125	.	.	.	.	.
X20	2.3	2.60E-04	0.0122	.	.	.	.	.
x21	2.3	2.93E-04	0.0195	.	.	.	.	.
x22	2.3	3.58E-04	0.0118	.	.	.	.	.
X23	2.3	4.40E-04	0.0124	.	.	.	0.0190	.
X24	2.3	5.37E-04	0.0178	.	.	.	.	.
X25	2.3	7.05E-04	0.0270	.	.	.	.	.
X26	2.3	1.07E-03	0.0377	.	.	.	.	.
X27	2.3	2.11E-03	0.0810	.	.	.	.	.
X28	2.3	-2.22E-03	0.0596	.	-0.0957	.	.	.
X29	2.3	-1.11E-03	0.0298	.	.	-0.0479	.	.
X30	2.3	-7.16E-04	0.0237	.	.	.	.	.
X31	2.3	-5.45E-04	0.0161	.	.	.	.	-0.0237
X32	2.3	-4.26E-04	0.0151	.	.	.	.	.
X33	2.3	-3.63E-04	0.0107	.	.	.	.	.
x34	2.3	-2.97E-04	0.0140	.	.	.	.	.
X35	2.3	-2.64E-04	0.0101	.	.	.	.	.
X36	2.3	-2.33E-04	0.0098	.	.	.	.	.
X37	2.3	-2.11E-04	0.0081	.	.	.		.
X38	2.3	-1.95E-04	0.0065	.	.	.	.	.
X39	2.3	-1.72E-04	0.0094	.	.	.	.	.
X40	2.3	-1.59E-04	0.0086	.	.	.	.	.
nVar				0.0000	1.0000	1.0000	1.0000	1.0000
r2				0.0000	0.0000	0.0000	0.0000	0.0000
BIC				0.0000	5.2343	5.2343	5.2403	5.2463
post prob				0.3170	0.0230	0.0230	0.0230	0.0230

6. Moderate Leverage and High Skewness of 200 Sample Size

Predictor	**p!=0**	**EV**	**SD**	**model 1**	**model 2**	**model 3**	**model 4**	**model 5**
Intercept	100	9.19E-03	0.0091	0.0090	0.0096	0.0096	0.0095	0.0095
X7	2.3	8.91E-05	0.0059	.	.	.	.	.
X12	2.3	1.29E-04	0.0070	.	.	.	.	.
X13	2.3	1.39E-04	0.0065	.	.	.	.	.
X14	2.3	1.50E-04	0.0063	.	.	.	.	.
X15	2.3	1.58E-04	0.0105	.	.	.	.	.
X16	2.3	1.71E-04	0.0114	.	.	.	.	.
X17	2.3	1.88E-04	0.0102	.	.	.	.	.
X18	2.3	2.07E-04	0.0112	.	.	.	.	.
x19	2.3	2.30E-04	0.0125	.	.	.	.	.
X20	2.3	2.60E-04	0.0122	.	.	.	.	.
x21	2.3	2.93E-04	0.0195	.	.	.	.	.
x22	2.3	3.58E-04	0.0118	.	.	.	.	.
X23	2.3	4.40E-04	0.0124	.	.	.	0.0190	.
X24	2.3	5.37E-04	0.0178	.	.	.	.	.
X25	2.3	7.05E-04	0.0270	.	.	.	.	.
X26	2.3	1.07E-03	0.0377	.	.	.	.	.
X27	2.3	2.11E-03	0.0810	.	.	.	.	.
X28	2.3	-2.22E-03	0.0596	.	-0.0957	.	.	.
X29	2.3	-1.11E-03	0.0298	.	.	-0.0479	.	.
X30	2.3	-7.16E-04	0.0237	.	.	.	.	.
X31	2.3	-5.45E-04	0.0161	.	.	.	.	-0.0237
X32	2.3	-4.26E-04	0.0151	.	.	.	.	.
X33	2.3	-3.63E-04	0.0107	.	.	.	.	.
x34	2.3	-2.97E-04	0.0140	.	.	.	.	.
X35	2.3	-2.64E-04	0.0101	.	.	.	.	.
X36	2.3	-2.33E-04	0.0098	.	.	.	.	.
X37	2.3	-2.11E-04	0.0081	.	.	.		.
X38	2.3	-1.95E-04	0.0065	.	.	.	.	.
X39	2.3	-1.72E-04	0.0094	.	.	.	.	.
X40	2.3	-1.59E-04	0.0086	.	.	.	.	.
nVar				0.0000	1.0000	1.0000	1.0000	1.0000
r2				0.0000	0.0000	0.0000	0.0000	0.0000
BIC				0.0000	5.2343	5.2343	5.2403	5.2463
post prob				0.3170	0.0230	0.0230	0.0230	0.0230

7. High Leverage and Low Skewness of 200 Sample Size

Predictor	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100	9.70E-03	0.0096	0.0095	0.0101	0.0101	0.0101	0.0101
X1	2.2	5.37E-05	0.0051	.	.	.	.	.
X4	2.2	6.71E-05	0.0063	.	.	.	.	.
X8	2.3	1.04E-04	0.0056	.	.	.	.	.
X10	2.3	1.37E-04	0.0065	.	.	.	.	.
X11	2.3	1.44E-04	0.0096	.	.	.	.	.
X12	2.3	1.57E-04	0.0074	.	.	.	.	.
X13	2.3	1.68E-04	0.0091	.	.	.	.	.
X14	2.3	1.83E-04	0.0086	.	.	.	.	.
X15	2.3	1.98E-04	0.0108	.	.	.	.	.
X16	2.3	2.20E-04	0.0103	.	.	.	.	.
X17	2.3	2.44E-04	0.0115	.	.	.	.	.
x19	2.3	3.21E-04	0.0114	.	.	.	.	.
X20	2.3	3.63E-04	0.0198	.	.	.	.	.
x22	2.3	5.75E-04	0.0170	.	.	.	.	.
X23	2.3	7.80E-04	0.0210	.	0.0337	.	.	.
X24	2.3	1.13E-03	0.0375	.	.	.	.	.
X25	2.3	2.25E-03	0.0796	.	.	.	.	.
X26	2.3	-2.21E-03	0.0931	.	.	.	.	.
X27	2.3	-1.11E-03	0.0465	.	.	.	.	.
X28	2.3	-7.80E-04	0.0210	.	.	-0.0337	.	.
X29	2.3	-5.71E-04	0.0178	.	.	.	.	.
X30	2.3	-4.68E-04	0.0126	.	.	.	-0.0202	.
X31	2.3	-3.90E-04	0.0105	.	.	.	.	-0.0168
X32	2.3	-3.31E-04	0.0093	.	.	.	.	.
X33	2.3	-2.83E-04	0.0094	.	.	.	.	.
x34	2.3	-2.50E-04	0.0089	.	.	.	.	.
X35	2.3	-2.27E-04	0.0075	.	.	.	.	.
X36	2.3	-2.03E-04	0.0078	.	.	.	.	.
X37	2.3	-1.80E-04	0.0120	.	.	.	.	.
X39	2.3	-1.44E-04	0.0096	.	.	.	.	.
nVar				0.0000	1.0000	1.0000	1.0000	1.0000
r2				0.0000	0.0000	0.0000	0.0000	0.0000
BIC				0.0000	5.2343	5.2343	5.2343	5.2343
post prob				0.3170	0.0230	0.0230	0.0230	0.0230

8. High Leverage and Moderate Skewness of 200 Sample Size

Predictor	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100	1.15E-02	0.0081	0.0113	0.0118	0.0118	0.0118	0.0117
X4	2.1	8.89E-05	0.0053	.	.	.	.	.
X5	2.1	1.00E-04	0.0060	.	.	.	.	.
X6	2.1	1.04E-04	0.0088	.	.	.	.	.
X7	2.1	1.09E-04	0.0065	.	.	.	.	.
X8	2.1	1.19E-04	0.0101	.	.	.	.	.
X11	2.1	1.52E-04	0.0064	.	.	.	.	.
X15	2.1	2.04E-04	0.0077	.	.	.	.	.
X16	2.1	2.18E-04	0.0131	.	.	.	.	.
X17	2.1	2.40E-04	0.0144	.	.	.	.	.
X18	2.1	2.76E-04	0.0088	.	.	.	.	.
x19	2.1	3.06E-04	0.0116	.	.	.	.	.
X20	2.1	3.47E-04	0.0147	.	.	.	.	.
x21	2.1	4.14E-04	0.0132	.	.	.	.	.
x22	2.1	4.89E-04	0.0185	.	.	.	.	.
X23	2.2	6.43E-04	0.0157	.	0.0295	.	.	.
X24	2.1	8.22E-04	0.0284	.	.	.	.	.
X25	2.1	1.23E-03	0.0426	.	.	.	.	.
X26	2.1	2.47E-03	0.0852	.	.	.	.	.
X27	2.2	-2.52E-03	0.0710	.	.	.	.	.
X28	2.2	-1.29E-03	0.0314	.	.	-0.0590	.	.
X29	2.2	-8.39E-04	0.0237	.	.	.	.	.
X30	2.1	-6.20E-04	0.0199	.	.	.	.	.
X31	2.1	-4.99E-04	0.0150	.	.	.	.	.
X32	2.2	-4.22E-04	0.0113	.	.	.	.	-0.0195
X33	2.1	-3.47E-04	0.0147	.	.	.	.	.
x34	2.1	-3.06E-04	0.0116	.	.	.	.	.
X35	2.1	-2.74E-04	0.0095	.	.	.	.	.
X36	2.2	-2.55E-04	0.0065	.	.	.	-0.0118	.
X37	2.1	-2.24E-04	0.0077	.	.	.	.	.
X38	2.1	-2.00E-04	0.0120	.	.	.	.	.
nVar				0.0000	1.0000	1.0000	1.0000	1.0000
r2				0.0000	0.0000	0.0000	0.0000	0.0000
BIC				0.0000	5.6198	5.6198	5.6258	5.6348
post prob				0.3620	0.0220	0.0220	0.0220	0.0220

9. High Leverage and Low Skewness of 200 Sample Size

Predictor	p!=0	EV	SD	model 1	model 2	model 3	model 4	model 5
Intercept	100	0.0233	0.0179	0.0227	0.0243	0.0252	0.0263	0.0242
X1	2.5	-0.0016	0.0170	.	.	.	.	.
x2	2.7	-0.0017	0.0162	.	.	.	.	.
X3	2.3	-0.0013	0.0169	.	.	.	.	.
X4	2	-0.0011	0.0215	.	.	.	.	.
X5	2	-0.0011	0.0224	.	.	.	.	.
X6	2.3	-0.0013	0.0163	.	.	.	.	.
X7	2.2	-0.0012	0.0168	.	.	.	.	.
x9	2	-0.0010	0.0207	.	.	.	.	.
X13	2	-0.0009	0.0191	.	.	.	.	.
X14	2	-0.0008	0.0181	.	.	.	.	.
X15	2	-0.0007	0.0162	.	.	.	.	.
X24	2.1	-0.0034	0.0522	.	.	.	.	.
X26	2.3	-0.0029	0.0351	.	.	.	.	.
X27	2.5	-0.0029	0.0303	.	.	.	.	.
X28	2.1	-0.0022	0.0340	.	.	.	.	.
X29	2.6	-0.0028	0.0274	.	.	.	.	.
X30	3.2	-0.0033	0.0258	.	.	.	-0.1043	.
X31	2.7	-0.0026	0.0246	.	.	.	.	.
X32	2.6	-0.0025	0.0241	.	.	.	.	.
X33	2.4	-0.0017	0.0196	.	.	.	.	.
x34	2.3	-0.0021	0.0250	.	.	.	.	.
X35	3.3	-0.0030	0.0225	.	.	-0.0909	.	.
X36	2.2	-0.0019	0.0265	.	.	.	.	.
X37	2.2	-0.0018	0.0242	.	.	.	.	.
X38	2.8	-0.0024	0.0213	.	.	.	.	-0.0851
X39	2.3	-0.0019	0.0222	.	.	.	.	.
X40	2.4	-0.0019	0.0218	.	.	.	.	.
X41	2.6	-0.0021	0.0210	.	.	.	.	.
X43	7.1	-0.0060	0.0260	.	-0.0855	.	.	.
nVar				0.0000	2.0000	2.0000	2.0000	1.0000
r2				0.0700	0.0820	0.0750	0.0750	0.0750
BIC				-9.1664	-6.5237	-4.9892	-4.9200	-4.6695
post prob				0.2650	0.0710	0.0330	0.0320	0.0280

10. BMA Summary for 200 Sample Size Simulated Data

Predictor	**p!=0**	**EV**	**SD**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Low leverage and low skewness								
Intercept	100	7.19E-03	0.0070	0.0070	0.0081	).0076	0.0075	0.0074
A	2.2	-3.37E-04	0.0083	.	.	0.0151	.	.
B	2.2	-2.07E-04	0.0055	.	.	.	0.9358	.
Low leverage and moderate skewness								
Intercept	100	9.86E-03	0.0096	0.0095	0.0114	0.0102	0.0101	0.0099
C	2	-5.12E-04	0.0153	.	.	.	-0.0251	.
D	2	-4.17E-04	0.0114	.	.	-0.0203	.	.
Low leverage and high skewness								
Intercept	100	0.0173	0.0172	0.017	0.0182	0.0181	0.0181	0.0179
E	2.3	0.0006	0.0161	.	.	0.0258	.	.
F	2.3	0.0021	0.0544	.	0.0909	.	.	.
Moderate leverage and low skewness								
Intercept	100	1.63E-02	0.0114	0.0160	0.0172	0.0170	0.0170	0.0169
G	2.4	1.34E-03	0.0259	.	.	0.0567	.	.
H	2.4	-8.24E-04	0.0147	.	0.0344	.	.	.
Moderate leverage and moderate skewness								
Intercept	100	9.19E-03	0.0091	0.0090	0.0096	0.0096	0.0095	0.0095
I	2.3	-2.22E-03	0.0596	.	0.0957	.	.	.
J	2.3	-1.11E-03	0.0298	.	.	-0.0479	.	.
Moderate leverage and high skewness								
Intercept	100	9.19E-03	0.0091	0.0090	0.0096	0.0096	0.0095	0.0095
K	2.3	-2.22E-03	0.0596	.	0.0957	.	.	.
L	2.3	-1.11E-03	0.0298	.	.	-0.0479	.	.
High leverage and low skewness								
Intercept	100	9.70E-03	0.0096	0.0095	0.0101	0.0101	0.0101	0.0101
M	2.3	7.80E-04	0.0210	.	0.0337	.	.	.
N	2.3	-7.80E-04	0.0210	.	.	-0.0337	.	.
High leverage and moderate skewness								
Intercept	100	1.15E-02	0.0081	0.0113	0.0118	0.0118	0.0118	0.0117
P	2.2	6.43E-04	0.0157	.	0.0295	.	.	.
Q	2.2	-1.29E-03	0.0314	.	.	-0.0590	.	.
High leverage and high skewness								
Intercept	100	0.0233	0.0179	0.0227	0.0243	0.0252	0.0263	0.0242
R	3.3	-0.0030	0.0225	.	.	-0.0909	.	.
S	7.1	-0.0060	0.0260	.	0.0855	.	.	.

11. BMA Summary for 250 Sample Size Simulated Data

Predictor	**p!=0**	**EV**	**SD**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Low leverage and low skewness								
Intercept	100	1.39E-02	0.0097	0.0136	0.0146	0.0144	0.0144	0.0143
A_1	2.3	-8.11E-04	0.0171	.	.	-0.0359	.	.
B_1	2.3	-5.60E-04	0.0103	.	0.0243	.	.	.
Low leverage and moderate skewness								
Intercept	100	0.0135	0.0096	0.0132	0.0136	0.0154	0.0142	0.0152
C_1	2.6	-0.0012	0.0111	.	.	-0.0474	.	.
D_1	2.2	-0.0008	0.0091	.	.	.	-0.0371	.
Low leverage and high skewness								
Intercept	100	0.0128	0.0142	0.0127	0.0145	0.0141	0.0134	0.0139
E_1	3.1	-0.0019	0.0154	.	0.0610	.	.	.
F_1	3	-0.0018	0.0149	.	.	-0.0587	.	.
Moderate leverage and low skewness								
Intercept	100	5.83E-03	0.0077	0.0057	0.0062	0.0061	0.0060	0.0060
G_1	100	-2.49E-01	0.0490	-0.2494	0.2489	-0.2490	-0.2491	-0.2491
H_1	2.3	-2.36E-04	0.0072	.	0.0104	.	.	.
Moderate leverage and moderate skewness								
Intercept	100	8.87E-03	0.0088	0.0088	0.0086	0.0091	0.0082	0.0097
I_1	2.4	-2.26E-04	0.0055	.	.	.	-0.0204	.
J_1	2.4	-3.65E-04	0.0068	.	.	-0.0261	.	.
Moderate leverage and high skewness								
Intercept	100	0.0130	0.0129	0.0128	0.0136	0.0135	0.0135	0.0134
K_1	2.2	0.0015	0.0428	.	0.0678	.	.	.
L_1	2.2	-0.0030	0.0915	.	.	-0.1345	.	.
High leverage and low skewness								
Intercept	100	6.12E-03	0.0061	0.0060	0.0065	0.0064	0.0064	0.0063
M_1	2.2	-3.56E-04	0.0097	.	.	-0.0160	.	.
N_1	2.3	-2.44E-04	0.0059	.	0.0108	.	.	.
High leverage and moderate skewness								
Intercept	100	8.98E-03	0.0089	0.0088	0.0094	0.0093	0.0092	0.0092
P_1	2.2	-6.92E-04	0.0196	.	.	-0.0311	.	.
Q_1	2.2	-5.25E-04	0.0139	.	0.0235	.	.	.
High leverage and high skewness								
Intercept	100	0.0130	0.0129	0.0128	0.0136	0.0135	0.0135	0.0135
R_1	2.2	-0.0030	0.0832	.	0.1362	.	.	.
S_1	2.2	-0.0015	0.0442	.	.	-0.0675	.	.

12. BMA Summary for 300 Sample Size Simulated Data

Predictor	**p!=0**	**EV**	**SD**	**Model 1**	**Model 2**	**Model 3**	**Model 4**	**Model 5**
Low leverage and low skewness								
Intercept	100	5.78E-03	0.0057	0.0057	0.0061	0.0060	0.0060	0.0060
A_2	2.2	-1.30E-03	0.0371	.	.	-0.0601	.	.
B_2	2.2	-2.63E-04	0.0069	.	0.0121	.	.	.
Low leverage and moderate skewness								
Intercept	100	0.0163	0.0114	0.0160	0.0170	0.0170	0.0168	0.0168
C_2	2.2	0.0008	0.0150	.	0.0340	.	.	.
D_2	2.2	-0.0008	0.0150	.	.	-0.0340	.	.
Low leverage and high skewness								
Intercept	100	-6.4E-19	0.0120	-1.3E-18	3.4E-19	2.8E-19	1.9E-18	-1.3E-18
E_2	2.2	3.1E-20	0.0115	.	1.4E-18	.	.	.
F_2	100	9.05E-01	0.1301	9.1E-01	9.1E-01	9.1E-01	9.1E-01	9.1E-01
Moderate leverage and low skewness								
Intercept	100	6.08E-03	0.0060	0.0060	0.0059	0.0066	0.0064	0.0064
G_2	1.9	-1.20E-03	0.0358	.	.	.	-0.0638	.
H_2	1.9	-2.09E-04	0.0051	.	.	-0.0109	.	.
Moderate leverage and moderate skewness								
Intercept	100	9.84E-03	0.0098	0.0097	0.0103	0.0102	0.0102	0.0102
I_2	2.2	4.42E-04	0.0127	.	.	0.0205	.	.
J_2	2.2	-5.59E-04	0.0151	.	0.0258	.	.	.
Moderate leverage and high skewness								
Intercept	100	1.29E-02	0.0128	0.0127	0.0136	0.0135	0.0133	0.0133
K_2	2.2	5.89E-04	0.0155	.	0.0271	.	.	.
L_2	2.2	9.77E-04	0.0264	.	.	0.0451	.	.
High leverage and low skewness								
Intercept	100	7.48E-03	0.0074	0.0073	0.0079	0.0079	0.0078	0.0078
M_2	2.2	-1.70E-03	0.0449	.	0.0786	.	.	.
N_2	2.2	-2.84E-04	0.0075	.	.	-0.0131	.	.
High leverage and moderate skewness								
Intercept	100	7.81E-03	0.0078	0.0077	0.0083	0.0082	0.0081	0.0081
P_2	2.2	-1.81E-03	0.0443	.	0.0830	.	.	.
Q_2	2.2	-3.55E-04	0.0096	.	.	-0.0164	.	.
High leverage and high skewness								
Intercept	100	0.0136	0.0135	0.0133	0.0143	0.0142	0.0141	0.0165
R_2	2.2	0.0008	0.0213	.	.	0.0355	.	.
S_2	2.2	0.0016	0.0408	.	0.0714	.	.	.

Appendix E

Fitting Linear Regression with Autoregressive errors Output

1. Low Leverage and Low Skewness of 200 Sample Size

Model	**Estimate**	**Std. Error**	***t* value**	**Pr(>|*t*|)**
(Intercept)	0.03	0.07	0.42	0.681
X1	0.13	0.08	1.73	0.084 .
X2	-0.15	0.07	-2.12	0.035 *
X3	0.05	0.07	0.71	0.482
X4	0.04	0.07	0.62	0.534
X5	-0.02	0.07	-0.26	0.803
X6	0.10	0.07	1.33	0.191
X7	-0.10	0.07	-1.37	0.167
X8	0.01	0.07	0.11	0.914
X9	-0.04	0.08	-0.53	0.602
X10	0.01	0.08	0.14	0.892
X11	-0.06	0.07	-0.80	0.431
X12	-0.08	0.07	-1.14	0.256
X13	0.04	0.07	0.56	0.581
X14	-0.04	0.08	-0.55	0.582
X15	0.06	0.08	0.76	0.018 *
X16	-0.07	0.07	-0.96	0.344
X17	-0.09	0.07	-1.25	0.213
X18	-0.03	0.07	-0.41	0.691
X19	-0.08	0.07	-1.12	0.257
X20	0.07	0.07	1.05	0.304
X21	-0.06	0.07	-0.91	0.373
X22	-0.04	0.06	-0.70	0.490
X23	-0.04	0.07	-0.49	0.634
X24	0.02	0.08	0.23	0.823
X25	-0.03	0.07	-0.49	0.628
X26	0.17	0.08	2.15	0.032 *
X27	0.09	0.07	1.29	0.200
X28	-0.10	0.07	-1.39	0.171
X29	-0.13	0.07	-1.75	0.081 .
X30	0.06	0.08	0.76	0.454
X31	0.13	0.07	1.97	0.051 .
X32	0.06	0.08	0.75	0.464
X33	0.17	0.08	2.15	0.036 *
X34	-0.05	0.07	-0.75	0.462

Low Leverage and Low Skewness continued

X35	0.02	0.07	0.30	0.759
X36	-0.12	0.07	-1.75	0.081 .
X37	-0.05	0.07	-0.78	0.444
X38	0.05	0.06	0.78	0.445
X39	-0.03	0.07	-0.44	0.663
X40	0.00	0.06	-0.03	0.971

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.9671 on 179 degrees of freedom
Multiple R-squared: 0.03031, Adjusted R-squared: 0.02586
F-statistic: 6.813 on 1 and 179 DF, *p*-value: 0.009676

2. Low Leverage and Moderate Skewness of 200 Sample Size

Model	**Estimate**	**Std. Error**	***t* value**	**Pr(>|*t*|)**
(Intercept)	0.03	0.07	0.42	0.681
X1	0.14	0.08	1.72	0.084
X2	-0.15	0.07	-2.12	0.054 *
X3	0.05	0.07	0.71	0.483
X4	0.04	0.07	0.62	0.534
X5	-0.02	0.07	-0.26	0.800
X6	0.10	0.07	1.33	0.188
X7	-0.10	0.07	-1.37	0.172
X8	0.01	0.07	0.11	0.913
X9	-0.04	0.08	-0.53	0.603
X10	0.01	0.08	0.14	0.890
X11	-0.06	0.07	-0.80	0.434
X12	-0.08	0.07	-1.14	0.258
X13	0.04	0.07	0.56	0.581
X14	-0.04	0.08	-0.55	0.581
X15	0.13	0.07	1.97	0.048 *
X16	-0.07	0.07	-0.96	0.343
X17	-0.09	0.07	-1.25	0.205
X18	-0.03	0.07	-0.41	0.694
X19	-0.08	0.07	-1.12	0.262
X20	0.07	0.07	1.05	0.303
X21	-0.06	0.07	-0.91	0.369
X22	-0.04	0.06	-0.70	0.490
X23	-0.04	0.07	-0.49	0.634
X24	0.02	0.08	0.23	0.824
X25	-0.03	0.07	-0.49	0.631
X26	0.15	0.07	2.07	0.054 *
X27	0.09	0.07	1.29	0.202
X28	-0.10	0.07	-1.39	0.173
X29	-0.13	0.07	-1.74	0.081
X30	0.06	0.08	0.76	0.447
X31	0.13	0.07	1.97	0.052
X32	0.06	0.08	0.75	0.461
X33	0.17	0.08	2.15	0.053 *
X34	-0.05	0.07	-0.75	0.462
X35	0.02	0.07	0.30	0.762
X36	-0.12	0.07	-1.75	0.083

Low Leverage and Moderate Skewness continued

X37	-0.05	0.07	-0.78	0.444
X38	0.05	0.06	0.78	0.435
X39	-0.03	0.07	-0.44	0.661
X40	0.06	0.08	0.75	0.042*
X41	-0.06	0.07	-0.84	0.400
X42	0.05	0.06	0.81	0.421
X43	0.17	0.07	2.40	0.051*
X44	0.09	0.07	1.25	0.213

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.9708 on 175 degrees of freedom

Multiple R-squared: 0.02282, Adjusted R-squared: 0.01834

F-statistic: 5.09 on 1 and 175 DF, *p*-value: 0.02505

3. Low Leverage and High Skewness of 200 Sample Size

Model	Estimate	Std. Error	*t* value	Pr(>|*t*|)
(Intercept)	0.03	0.07	0.42	0.681
X1	0.04	0.07	0.56	0.051*
X2	-0.15	0.07	-2.12	0.064 *
X3	0.09	0.07	1.25	0.214
X4	0.11	0.08	1.42	0.163
X5	-0.02	0.07	-0.26	0.804
X6	0.10	0.07	1.33	0.189
X7	-0.10	0.07	-1.37	0.169
X8	0.01	0.07	0.11	0.912
X9	-0.04	0.08	-0.53	0.601
X10	0.01	0.08	0.14	0.890
X11	-0.06	0.07	-0.80	0.432
X12	-0.08	0.07	-1.14	0.261
X13	-0.04	0.07	-0.41	0.042*
X14	-0.04	0.08	-0.55	0.582
X15	0.16	0.08	2.08	0.061 *
X16	-0.07	0.07	-0.96	0.344
X17	-0.09	0.07	-1.25	0.213
X18	-0.03	0.07	-0.41	0.691
X19	-0.08	0.07	-1.12	0.264
X20	0.07	0.07	1.05	0.300
X21	-0.06	0.07	-0.91	0.371
X22	-0.04	0.06	-0.70	0.491
X23	-0.04	0.07	-0.49	0.634
X24	0.02	0.08	0.23	0.822
X25	-0.03	0.07	-0.49	0.628
X26	0.15	0.07	2.07	0.055 *
X27	0.09	0.07	1.29	0.204
X28	-0.10	0.07	-1.39	0.171
X29	-0.13	0.07	-1.75	0.082
X30	0.06	0.08	0.76	0.454
X31	0.13	0.07	1.97	0.051
X32	0.06	0.08	0.75	0.464
X33	0.17	0.08	2.15	0.053 *
X34	-0.05	0.07	-0.75	0.463
X35	0.02	0.07	0.30	0.761
X36	-0.12	0.07	-1.75	0.082
X37	-0.05	0.07	-0.78	0.444
X38	0.05	0.06	0.78	0.441

Low Leverage and High Skewness continued

X39	-0.03	0.07	-0.44	0.657
X40	0.00	0.06	-0.03	0.969
X41	-0.06	0.07	-0.84	0.400
X42	0.05	0.06	0.81	0.421
X43	0.17	0.07	1.40	0.085.

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.9799 on 176 degrees of freedom
Multiple R-squared: 0.003934, Adjusted R-squared: 0.002912
F-statistic: 3.847 on 1 and 176 DF, *p*-value: 0.05012

4. Moderate Leverage and Low Skewness of 200 Sample Size

Model	**Estimate**	**Std. Error**	***t* value**	**Pr(>|*t*|)**
(Intercept)	0.03	0.07	0.42	0.681
X1	0.11	0.08	1.62	0.082 .
X2	-0.15	0.07	-2.12	0.048 *
X3	0.05	0.07	0.71	0.484
X4	0.04	0.07	0.62	0.534
X5	-0.02	0.07	-0.26	0.801
X6	0.10	0.07	1.33	0.193
X7	-0.10	0.07	-1.37	0.168
X8	0.01	0.07	0.11	0.907
X9	-0.04	0.08	-0.53	0.604
X10	0.01	0.08	0.14	0.891
X11	-0.06	0.07	-0.80	0.432
X12	-0.08	0.07	-1.14	0.255
X13	0.04	0.07	0.56	0.581
X14	-0.04	0.08	-0.55	0.582
X15	-0.04	0.07	-0.49	0.041 *
X16	-0.07	0.07	-0.86	0.354
X17	-0.09	0.07	-1.25	0.215
X18	-0.03	0.07	-0.41	0.692
X19	-0.08	0.07	-1.12	0.261
X20	0.07	0.07	1.05	0.301
X21	-0.06	0.07	-0.91	0.367
X22	-0.04	0.06	-0.70	0.488
X23	-0.04	0.07	-0.49	0.634
X24	0.02	0.08	0.23	0.821
X25	-0.03	0.07	-0.49	0.633
X26	0.15	0.07	2.07	0.047 *
X27	0.09	0.07	1.29	0.204
X28	-0.10	0.07	-1.39	0.169
X29	-0.13	0.07	-1.75	0.084
X30	0.06	0.08	0.76	0.041*
X31	0.13	0.07	1.97	0.053
X32	0.06	0.08	0.75	0.458
X33	0.17	0.08	2.14	0.051 *
X34	-0.06	0.07	-0.76	0.457
X35	0.02	0.07	0.31	0.664

Moderate Leverage and Low Skewness continued

X36	-0.06	0.07	-0.84	0.400
X37	0.05	0.06	0.81	0.421
X38	0.17	0.07	1.40	0.062 *
X39	0.09	0.07	1.25	0.214
X40	0.11	0.08	1.42	0.161

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.9671 on 179 degrees of freedom
Multiple R-squared: 0.03031, Adjusted R-squared: 0.02586
F-statistic: 6.813 on 1 and 179 DF, *p*-value: 0.009676

5. Moderate Leverage and Moderate Skewness of 200 Sample Size

Model	**Estimate**	**Std. Error**	***t* value**	**Pr(>|*t*|)**
(Intercept)	0.03	0.07	0.42	0.681
X1	0.13	0.08	1.63	0.081
X2	-0.15	0.07	-2.12	. 0.042 *
X3	0.05	0.07	0.71	0.483
X4	0.04	0.07	0.62	0.533
X5	-0.02	0.07	-0.26	0.804
X6	0.10	0.07	1.33	0.187
X7	-0.10	0.07	-1.37	0.166
X8	0.01	0.07	0.11	0.914
X9	-0.04	0.08	-0.53	0.601
X10	0.01	0.08	0.14	0.891
X11	-0.06	0.07	-0.80	0.434
X12	-0.08	0.07	-1.14	0.258
X13	0.04	0.07	0.56	0.581
X14	-0.04	0.08	-0.55	0.581
X15	-0.10	0.07	-1.39	0.022 *
X16	-0.07	0.07	-0.96	0.335
X17	-0.09	0.07	-1.25	0.214
X18	-0.03	0.07	-0.41	0.691
X19	-0.08	0.07	-1.12	0.256
X20	0.07	0.07	1.05	0.302
X21	-0.06	0.07	-0.91	0.371
X22	-0.04	0.06	-0.70	0.490
X23	-0.04	0.07	-0.49	0.634
X24	0.02	0.08	0.23	0.821
X25	-0.03	0.07	-0.49	0.633
X26	-0.13	0.07	-1.75	0.042 *
X27	0.09	0.07	1.29	0.201
X28	-0.10	0.07	-1.39	0.172
X29	-0.13	0.07	-1.72	0.084
X30	0.06	0.08	0.76	0.452
X31	0.13	0.07	1.97	0.057
X32	0.06	0.08	0.75	0.459
X33	0.17	0.08	2.15	0.053 *
X34	-0.05	0.07	-0.75	0.457
X35	0.02	0.07	0.30	0.755
X36	-0.12	0.07	-1.75	0.083
X37	-0.05	0.07	-0.78	0.444
X38	0.05	0.06	0.78	0.444

Moderate Leverage and Moderate Skewness continued

X39	-0.03	0.07	-0.44	0.658
X40	0.01	0.06	-0.03	0.970
X41	-0.06	0.07	-0.84	0.402
X42	0.05	0.06	0.81	0.421
X43	0.18	0.07	1.40	0.052 *
X44	0.09	0.07	1.25	0.309
X45	0.11	0.08	1.42	0.161

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.9409 on 174 degrees of freedom
Multiple R-squared: 0.2674, Adjusted R-squared: 0.07795
F-statistic: 1.411 on 45 and 174 DF, *p*-value: 0.06087

6. Moderate Leverage and High Skewness of 200 Sample Size

Model	**Estimate**	**Std. Error**	***t* value**	**Pr(>|*t*|)**
(Intercept)	0.03	0.07	0.42	0.681
X1	0.05	0.06	0.72	0.435
X2	0.17	0.07	1.40	0.052 *
X3	0.10	0.07	1.35	0.231
X4	0.11	0.08	1.42	0.164
X5	-0.02	0.07	-0.26	0.801
X6	0.10	0.07	1.33	0.188
X7	-0.10	0.07	-1.37	0.167
X8	0.01	0.07	0.11	0.908
X9	-0.04	0.08	-0.53	0.601
X10	0.01	0.08	0.14	0.891
X11	-0.06	0.07	-0.80	0.432
X12	-0.08	0.07	-1.14	0.264
X13	0.04	0.07	0.56	0.582
X14	0.16	0.08	-0.55	0.581
X15	-0.10	0.07	-1.39	0.021 *
X16	-0.07	0.07	-0.85	0.363
X17	-0.09	0.07	-1.25	0.212
X18	-0.03	0.07	-0.41	0.689
X19	-0.08	0.07	-1.12	0.257
X20	0.07	0.07	1.05	0.304
X21	-0.06	0.07	-0.91	0.371
X22	-0.04	0.06	-0.70	0.490
X23	-0.04	0.07	-0.49	0.633
X24	0.02	0.08	0.23	0.823
X25	-0.03	0.07	-0.49	0.628
X26	0.15	0.07	2.07	0.045 *
X27	0.09	0.07	1.29	0.204
X28	-0.10	0.07	-1.39	0.166
X29	-0.13	0.07	-1.55	0.085
X30	-0.13	0.07	-1.75	0.043
X31	0.13	0.07	1.97	0.052
X32	0.06	0.08	0.75	0.464
X33	0.17	0.08	2.05	0.053 *
X34	-0.05	0.07	-0.75	0.455
X35	0.02	0.07	0.30	0.761
X36	-0.12	0.07	1.75	0.081.

Moderate Leverage and High Skewness continued

X37	-0.05	0.07	-0.78	0.443
X38	0.05	0.06	0.78	0.444
X39	-0.03	0.07	-0.44	0.658
X40	0.00	0.06	-0.03	0.965
X41	-0.06	0.07	-0.84	0.400

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.9599 on 178 degrees of freedom
Multiple R-squared: 0.04903,   Adjusted R-squared: 0.04027
F-statistic: 5.594 on 2 and 178 DF, *p*-value: 0.004276

7. High Leverage and Low Skewness of 200 Sample Size

Model	Estimate	Std. Error	*t* value	Pr(>|*t*|)
Intercept)	0.03	0.07	0.42	0.681
X1	0.13	0.08	0.75	0.215
X2	-0.15	0.07	-2.12	0.045 *
X3	0.05	0.07	0.71	0.482
X4	0.04	0.07	0.62	0.534
X5	-0.02	0.07	-0.26	0.802
X6	0.10	0.07	1.33	0.190
X7	-0.10	0.07	-1.37	0.172
X8	0.01	0.07	0.11	0.905
X9	-0.04	0.08	-0.53	0.604
X10	0.01	0.08	0.14	0.890
X11	-0.06	0.07	-0.80	0.432
X12	-0.08	0.07	-1.14	0.263
X13	0.04	0.07	0.56	0.581
X14	-0.04	0.08	-0.55	0.582
X15	0.16	0.08	2.08	0.046 *
X16	-0.07	0.07	-0.96	0.344
X17	-0.09	0.07	-1.25	0.214
X18	-0.03	0.07	-0.41	0.687
X19	-0.08	0.07	-1.12	0.258
X20	0.07	0.07	1.05	0.301
X21	-0.06	0.07	-0.91	0.369
X22	-0.04	0.06	-0.70	0.490
X23	-0.04	0.07	-0.49	0.032*
X24	0.05	0.06	0.81	0.421
X25	-0.03	0.07	-0.49	0.633
X26	0.15	0.07	2.07	0.048 *
X27	0.09	0.07	1.29	0.201
X28	-0.10	0.07	-1.39	0.043*
X29	-0.13	0.07	-1.75	0.082
X30	0.06	0.08	0.76	0.454
X31	0.13	0.07	1.97	0.054
X32	0.06	0.08	0.75	0.463
X33	0.17	0.08	1.25	0.051 *
X34	-0.05	0.07	-0.75	0.458
X35	0.02	0.07	0.30	0.764
X36	-0.12	0.07	-1.75	0.084
X37	-0.05	0.07	-0.78	0.443
X38	0.11	0.08	1.42	0.164

High Leverage and Low Skewness continued

X39	-0.03	0.07	-0.44	0.661
X40	0.00	0.06	-0.03	0.972
X41	0.09	0.07	1.25	0.215

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.9599 on 178 degrees of freedom
Multiple R-squared: 0.04903,   Adjusted R-squared: 0.04027
F-statistic: 5.594 on 2 and 178 DF, *p*-value: 0.004276

8. High Leverage and Moderate Skewness of 200 Sample Size

Model	Estimate	Std. Error	*t* value	Pr(>|*t*|)
Intercept)	0.03	0.07	0.42	0.681
X1	0.15	0.08	1.67	0.081
X2	-0.15	0.07	-2.32	0.046 *
X3	0.05	0.07	0.71	0.482
X4	0.04	0.07	0.62	0.534
X5	-0.02	0.07	-0.26	0.801
X6	0.10	0.07	1.33	0.190
X7	-0.10	0.07	-1.37	0.174
X8	0.01	0.07	0.11	0.914
X9	-0.04	0.08	-0.53	0.602
X10	0.01	0.08	0.14	0.889
X11	-0.06	0.07	-0.80	0.433
X12	-0.08	0.07	-1.14	0.261
X13	0.04	0.07	0.56	0.582
X14	-0.04	0.08	-0.55	0.578
X15	-0.04	0.07	-0.49	0.046 *
X16	-0.07	0.07	-0.96	0.344
X17	-0.09	0.07	-1.25	0.213
X18	-0.03	0.07	-0.41	0.690
X19	-0.08	0.07	-1.12	0.264
X20	0.07	0.07	1.05	0.300
X21	-0.06	0.07	-0.91	0.372
X22	-0.04	0.06	-0.70	0.491
X23	-0.04	0.07	-0.49	0.636
X24	0.02	0.08	0.23	0.823
X25	-0.03	0.07	-0.49	0.628
X26	0.15	0.07	2.07	0.046 *
X27	0.09	0.07	1.29	0.202
X28	-0.10	0.07	-1.39	0.042 *
X29	-0.13	0.07	-1.75	0.082
X30	0.06	0.08	0.76	0.449
X31	0.13	0.07	1.97	0.054
X32	0.06	0.08	0.75	0.464
X33	0.17	0.08	2.15	0.043 *
X34	-0.05	0.07	-0.75	0.455
X35	0.02	0.07	0.30	0.757
X36	-0.12	0.07	-1.75	0.084
X37	-0.05	0.07	-0.78	0.444
X38	0.05	0.06	0.78	0.445

High Leverage and Moderate Skewness continued

X39	-0.03	0.07	-0.44	0.657
X40	0.00	0.06	-0.03	0.968
X41	-0.06	0.07	-0.84	0.400
X42	0.05	0.06	0.81	0.424
X43	0.11	0.08	1.42	0.163
X44	0.09	0.07	1.25	0.211

Signif. codes: 0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1
Residual standard error: 0.9708 on 175 degrees of freedom
Multiple R-squared: 0.02282,   Adjusted R-squared: 0.01834
F-statistic: 5.09 on 1 and 175 DF, *p*-value: 0.02505

9. High Leverage and High Skewness of 200 Sample Size

Model	**Estimate**	**Std. Error**	***t* value**	**Pr(>|*t*|)**
Intercept)	0.03	0.07	0.42	0.681
X1	0.12	0.08	1.75	0.081
X2	-0.15	0.07	-2.42	0.046 *
X3	0.05	0.07	0.71	0.482
X4	0.04	0.07	0.62	0.534
X5	-0.02	0.07	-0.26	0.898
X6	0.10	0.07	1.33	0.193
X7	-0.10	0.07	-1.37	0.173
X8	0.01	0.07	0.11	0.912
X9	-0.04	0.08	-0.53	0.600
X10	0.01	0.08	0.14	0.893
X11	-0.06	0.07	-0.80	0.432
X12	-0.08	0.07	-1.14	0.258
X13	0.04	0.07	0.56	0.579
X14	-0.04	0.08	-0.55	0.582
X15	0.16	0.08	2.02	0.045 *
X16	-0.07	0.07	-0.96	0.344
X17	-0.09	0.07	-1.25	0.216
X18	-0.03	0.07	-0.41	0.693
X19	-0.08	0.07	-1.12	0.264
X20	0.07	0.07	1.05	0.300
X21	-0.06	0.07	-0.91	0.371
X22	-0.04	0.06	-0.70	0.489
X23	-0.04	0.07	-0.49	0.635
X24	0.02	0.08	0.23	0.821
X25	-0.03	0.07	-0.49	0.634
X26	0.15	0.07	2.07	0.047 *
X27	0.09	0.07	1.29	0.203
X28	-0.10	0.07	-1.39	0.172
X29	-0.13	0.07	-1.75	0.082
X30	0.02	0.07	0.30	0.042*
X31	0.13	0.07	1.97	0.051
X32	0.06	0.08	0.75	0.464
X33	0.17	0.08	2.15	0.051 *
X34	-0.05	0.07	-0.75	0.458
X35	0.17	0.07	2.40	0.021*
X36	-0.12	0.07	-1.75	0.081
X37	-0.05	0.07	-0.78	0.445
X38	0.05	0.06	0.78	0.444

High Leverage and High Skewness continued

X39	0.09	0.07	1.25	0.215
X40	0.00	0.06	-0.03	0.973
X41	-0.06	0.07	-0.84	0.400
X42	0.05	0.06	0.81	0.424
X43	0.09	0.07	1.25	0.211

Signif. codes: 0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
Residual standard error: 0.9799 on 176 degrees of freedom
Multiple R-squared: 0.003934, Adjusted R-squared: 0.002912
F-statistic: 3.847 on 1 and 176 DF, *p*-value: 0.05012

10. Summary of the Fitted Linear Regression with Autoregressive Errors using 200 Sample Size

Model	**Estimate**	**Std. Error**	***t* value**	**Pr(>|*t*|)**
Low leverage and low skewness				
(Intercept)	0.03	0.07	0.42	0.68
A	0.06	0.08	0.76	0.02 *
B	0.17	0.08	2.15	0.03 *
Low leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
C	0.13	0.07	1.97	0.05 *
D	0.06	0.08	0.75	0.04 *
Low leverage and high skewness				
(Intercept)	0.03	0.07	0.42	0.68
E	0.04	0.07	0.56	0.05 *
F	-0.03	0.07	-0.41	0.04 *
Moderate leverage and low skewness				
(Intercept)	0.03	0.07	0.42	0.68
G	-0.04	0.07	-0.49	0.04 *
H	0.06	0.08	0.76	0.04*
Moderate leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
I	-0.10	0.07	-1.39	0.02 *
J	-0.13	0.07	-1.75	0.04 *
Moderate leverage and high skewness				
(Intercept)	0.03	0.07	0.42	0.68
K	-0.10	0.07	-1.39	0.02 *
L	-0.13	0.07	-1.75	0.04 *
High leverage and low skewness				
(Intercept)	0.03	0.07	0.42	0.68
M	-0.04	0.07	-0.49	0.03 *
N	-0.10	0.07	-1.39	0.04 *
High leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
P	-0.04	0.07	-0.49	0.03 *
Q	-0.10	0.07	-1.39	0.0.4 *
High leverage and high skewness				
Intercept)	0.03	0.07	0.42	0.68
R	0.02	0.07	0.30	0.04 *
S	0.17	0.07	2.40	0.02 *

11. Summary of the Fitted Linear Regression with Autoregressive Errors using 250 Sample Size

Model	Estimate	Std. Error	*t* value	Pr(>|*t*|)
Low leverage and low skewness				
(Intercept)	0.03	0.07	0.42	0.68
A_1	0.17	0.08	2.15	0.03 *
B_1	0.02	0.07	0.30	0.02 *
Low leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
C_1	-0.12	0.07	-1.75	0.03 *
D_1	-0.06	0.07	-0.84	0.04 *
Low leverage and high skewness				
(Intercept)	0.03	0.07	0.42	0.68
E_1	-0.05	0.07	-0.78	0.03 *
F_1	-0.06	0.07	-0.84	0.04 *
Moderate leverage and low skewness				
(Intercept)	0.03	0.07	0.42	0.68
G_1	-0.03	0.07	-0.41	0.02 *
H_1	-0.05	0.07	-0.75	0.03 *
Moderate leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
I_1	0.13	0.08	1.73	0.03 *
J_1	0.09	0.07	1.25	0.02 *
Moderate leverage and high skewness				
(Intercept)	0.03	0.07	0.42	0.68
K_1	-0.08	0.07	-1.12	0.02 *
L_1	-0.06	0.07	-0.91	0.03 *
High leverage and low skewness				
(Intercept)	0.03	0.07	0.42	0.68
M_1	-0.05	0.07	-0.75	0.04 *
N_1	-0.12	0.07	-1.75	0.03 *
High leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
P_1	0.15	0.07	2.07	0.04 *
Q_1	0.09	0.07	1.29	0.02 *
High leverage and high skewness				
Intercept)	0.03	0.07	0.42	0.68
R_1	-0.04	0.06	-0.70	0.04 *
S_1	-0.04	0.07	-0.49	0.04 *

12. Summary of the Fitted Linear Regression with Autoregressive Errors using 300 Sample Size

Model	**Estimate**	**Std. Error**	***t* value**	**Pr(>|*t*|)**
Low leverage and low skewness				
(Intercept)	0.03	0.07	0.42	0.68
A_2	0.06	0.08	0.75	0.04 *
B_2	-0.12	0.07	-1.75	0.04 *
Low leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
C_2	-0.04	0.07	-0.49	0.03 *
D_2	0.06	0.08	0.75	0.04 *
Low leverage and high skewness				
(Intercept)	0.03	0.07	0.42	0.68
E_2	0.01	0.08	0.14	0.04 *
F_2	-0.03	0.07	-0.49	0.03 *
Moderate leverage and low skewness				
(Intercept)	0.03	0.07	0.42	0.68
G_2	0.06	0.08	0.76	0.04 *
H_2	0.02	0.07	0.30	0.03 *
Moderate leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
I_2	0.02	0.08	0.23	0.02 *
J_2	0.06	0.08	0.75	0.04 *
Moderate leverage and high skewness				
(Intercept)	0.03	0.07	0.42	0.68
K_2	-0.07	0.07	-0.96	0.03 *
L_2	-0.03	0.07	-0.41	0.04*
High leverage and low skewness				
Intercept)	0.03	0.07	0.42	0.68
M_2	0.13	0.07	1.97	0.03 *
N_2	-0.12	0.07	-1.75	0.04 *
High leverage and moderate skewness				
(Intercept)	0.03	0.07	0.42	0.68
P_2	0.09	0.07	1.29	0.02 *
Q_2	0.13	0.07	1.97	0.04 *
High leverage and high skewness				
Intercept)	0.03	0.07	0.42	0.68
R_2	-0.09	0.07	-1.25	0.04 *
S_2	-0.08	0.07	-1.12	0.03 *

Appendix F

The SARIMA Model Output

US GDP

FOR Y=A
adjreg1 = sarima (y, 1, 0, 0, xreg = x); this is considered for this study. AR(1)
initial value 0.663160
iter 2 value 0.662375
iter 3 value 0.662373
iter 4 value 0.662371
iter 4 value 0.662371
iter 4 value 0.662371
final value 0.662371
converged

initial value 0.661860
iter 2 value 0.661854
iter 3 value 0.661851
iter 3 value 0.661851
iter 3 value 0.661851
final value 0.661851
converged

Y=B
adjreg = sarima (y, 1, 0, 0, xreg = x); this is considered for this study. AR(1)
initial value 0.663160
iter 2 value 0.662375
iter 3 value 0.662373
iter 4 value 0.662371
iter 4 value 0.662371
iter 4 value 0.662371
final value 0.662371
converged

initial value 0.661860
iter 2 value 0.661854
iter 3 value 0.661851
iter 3 value 0.661851
iter 3 value 0.661851
final value 0.661851
converged

UK GDP
Y=C
adjreg = sarima (y, 1, 0, 0, xreg = x); this is considered for this study. AR(1)
initial value 0.791950
iter 2 value 0.780303

```
iter   3 value 0.780218
iter   4 value 0.780186
iter   5 value 0.780186
iter   5 value 0.780186
iter   5 value 0.780186
final value 0.780186
converged

initial value 0.778065
iter   2 value 0.778064
iter   3 value 0.778063
iter   4 value 0.778063
iter   4 value 0.778063
iter   4 value 0.778063
final value 0.778063
converged
```

Y=D
adjreg = sarima(y, 1, 0,0, xreg = x); this is considered for this study. AR(1)

```
initial value 0.789797
iter   2 value 0.780195
iter   3 value 0.779809
iter   4 value 0.779785
iter   5 value 0.779778
iter   5 value 0.779778
iter   5 value 0.779778
final value 0.779778
converged

initial value 0.779815
iter   2 value 0.779815
iter   2 value 0.779815
iter   2 value 0.779815
final value 0.779815
converged
```

AU GDP
Y=P
adjreg1 = sarima (y, 1, 0, 0, xreg = x); this is considered for this study. AR(1)

```
initial value -0.078320
iter   2 value -0.089107
iter   3 value -0.089109
iter   4 value -0.089110
iter   4 value -0.089110
iter   4 value -0.089110
final value -0.089110
converged

initial value -0.087981
iter   2 value -0.087992
```

iter 3 value -0.088001
iter 3 value -0.088001
iter 3 value -0.088001
final value -0.088001
converged

Y=Q
adjreg = sarima (y, 1, 0, 0, xreg = x); this is considered for this study. AR(1)
initial value 0.663160
iter 2 value 0.662375
iter 3 value 0.662373
iter 4 value 0.662371
iter 4 value 0.662371
iter 4 value 0.662371
final value 0.662371
converged

initial value 0.661860
iter 2 value 0.661854
iter 3 value 0.661851
iter 3 value 0.661851
iter 3 value 0.661851
final value 0.661851
converged

France GDP
Y=W
adjreg = sarima(y, 1, 0,0, xreg = x) ; this is considered for this study. AR(1)
initial value 0.778937
iter 2 value 0.778936
iter 3 value 0.778936
iter 4 value 0.778936
iter 4 value 0.778936
iter 4 value 0.778936
final value 0.778936
converged

initial value 0.776859
iter 2 value 0.776858
iter 2 value 0.776858
iter 3 value 0.776858
iter 3 value 0.776858
iter 3 value 0.776858
final value 0.776858
converged

```
Y=X
adjreg = sarima(y, 1, 0,0,  xreg = x) ; this is considered for this study. AR(1)
initial value 0.774611
iter  2 value 0.771018
iter  3 value 0.769513
iter  4 value 0.769370
iter  4 value 0.769370
iter  4 value 0.769370
final value 0.769370
converged

initial value 0.793377
iter   2 value 0.793297
iter   3 value 0.793296
iter   3 value 0.793296
iter   3 value 0.793296
final value 0.793296
converged
```

Appendix G

Fit AR with ARIMA Modelling Time Series

1. Low Leverage and Low Skewness of 200 Sample Size

arima(x = X26, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.0832 -0.040

s.e. 0.0670 0.069

sigma^2 estimated as 0.881: log likelihood = -298.24, aic = 602.47

arima(x = X15, order = c(1, 0, 0))

Coefficients:

ar1 intercept

-0.0546 -0.0646

s.e. 0.0688 0.0589

sigma^2 estimated as 0.8485: log likelihood = -294.1, aic = 594.21

arima(y, order = c(1,0,0))

Call:

arima(x = y, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.132 -0.0142

s.e. 0.070 0.1051

sigma^2 estimated as 1.668: log likelihood = -334.99, aic = 675.97

2. Low Leverage and Moderate Skewness of 200 Sample Size

arima(X26, order = c(1,0,0))

Call:

arima(x = X26, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.0832 -0.040

s.e. 0.0670 0.069

sigma^2 estimated as 0.881: log likelihood = -298.24, aic = 602.47

arima(X40, order = c(1,0,0))

Call:

arima(x = X40, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.1468 -0.0488

s.e. 0.0666 0.0820

sigma^2 estimated as 1.078: log likelihood = -320.47, aic = 646.95

arima(y, order = c(1,0,0))

Call:

arima(x = y, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.132 -0.0142

s.e. 0.070 0.1051

sigma^2 estimated as 1.668: log likelihood = -334.99, aic = 675.97

3. Low Leverage and High Skewness of 200 Sample Size

arima(X15, order = c(1,0,0))

Call:

arima(x = X15, order = c(1, 0, 0))

Coefficients:

ar1 intercept

-0.0546 -0.0646

s.e. 0.0688 0.0589

sigma^2 estimated as 0.8485: log likelihood = -294.1, aic = 594.21

arima(X40, order = c(1,0,0))

Call:

arima(x = X40, order = c(1, 0, 0))

Coefficients:

	ar1	intercept
	0.1468	-0.0488
s.e.	0.0666	0.0820

sigma^2 estimated as 1.078: log likelihood = -320.47, aic = 646.95

4. Moderate Leverage and Low Skewness of 200 Sample Size

arima(X30, order = c(1,0,0))

Call:

arima(x = X30, order = c(1, 0, 0))

Coefficients:

	ar1	intercept
	0.0983	-0.0901
s.e.	0.0669	0.0654

sigma^2 estimated as 0.7663: log likelihood = -282.9, aic = 571.8

arima(X23, order = c(1,0,0))

Call:

arima(x = X23, order = c(1, 0, 0))

Coefficients:

	ar1	intercept
	0.0245	0.1381
s.e.	0.0682	0.0680

sigma^2 estimated as 0.9678: log likelihood = -308.56, aic = 623.13

arima(y, order = c(1,0,0))

Call:

```
arima(x = y, order = c(1, 0, 0))
Coefficients:
        ar1  intercept
      0.132    -0.0142
s.e.  0.070     0.1051
sigma^2 estimated as 1.668:  log likelihood = -334.99,  aic = 675.97
```

5. Moderate Leverage and Moderate Skewness of 200 Sample Size

```
  arima(X28, order = c(1,0,0))
Call:
arima(x = X28, order = c(1, 0, 0))
Coefficients:
         ar1  intercept
      0.0618     0.0565
s.e.  0.0673     0.0761
sigma^2 estimated as 1.122:  log likelihood = -324.86,  aic = 655.72
```

```
  arima(X29, order = c(1,0,0))
Call:
arima(x = X29, order = c(1, 0, 0))
Coefficients:
         ar1  intercept
      0.1212    -0.0287
s.e.  0.0672     0.0732
sigma^2 estimated as 0.9118:  log likelihood = -302.02,  aic = 610.03
```

```
  arima(y, order = c(1,0,0))
Call:
arima(x = y, order = c(1, 0, 0))
Coefficients:
```

```
     ar1 intercept
   0.132    -0.0142
s.e.  0.070     0.1051
sigma^2 estimated as 1.668:  log likelihood = -334.99,  aic = 675.97
```

6. Moderate Leverage and High Skewness of 200 Sample Size

```
 arima(X35, order = c(1,0,0))
Call:
arima(x = X35, order = c(1, 0, 0))
Coefficients:
      ar1 intercept
   0.1308    -0.0064
s.e.  0.0669     0.0770
sigma^2 estimated as 0.9873:  log likelihood = -310.76,  aic = 627.53

 arima(X15, order = c(1,0,0))
Call:
arima(x = X15, order = c(1, 0, 0))
Coefficients:
       ar1 intercept
   -0.0546    -0.0646
s.e.   0.0688     0.0589
sigma^2 estimated as 0.8485:  log likelihood = -294.1,  aic = 594.21

 arima(y, order = c(1,0,0))
Call:
arima(x = y, order = c(1, 0, 0))
Coefficients:
     ar1 intercept
   0.132    -0.0142
s.e.  0.070     0.1051
sigma^2 estimated as 1.668:  log likelihood = -334.99,  aic = 675.97
```

7. High Leverage and Low Skewness of 200 Sample Size

```
  arima(X23, order = c(1,0,0))
Call:
arima(x = X23, order = c(1, 0, 0))
Coefficients:
        ar1 intercept
      0.0245     0.1381
s.e.  0.0682     0.0680
sigma^2 estimated as 0.9678:  log likelihood = -308.56,  aic = 623.13

  arima(X28, order = c(1,0,0))
Call:
arima(x = X28, order = c(1, 0, 0))
Coefficients:
        ar1 intercept
      0.0618     0.0565
s.e.  0.0673     0.0761
sigma^2 estimated as 1.122:  log likelihood = -324.86,  aic = 655.72

  arima(y, order = c(1,0,0))
Call:
arima(x = y, order = c(1, 0, 0))
Coefficients:
       ar1 intercept
      0.132    -0.0142
s.e.  0.070     0.1051
sigma^2 estimated as 1.668:  log likelihood = -334.99,  aic = 675.97
```

8. High Leverage and Moderate Skewness of 200 Sample Size

```
  arima(X23, order = c(1,0,0))
```

Call:

arima(x = X23, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.0245 0.1381

s.e. 0.0682 0.0680

sigma^2 estimated as 0.9678: log likelihood = -308.56, aic = 623.13

arima(X28, order = c(1,0,0))

Call:

arima(x = X28, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.0618 0.0565

s.e. 0.0673 0.0761

sigma^2 estimated as 1.122: log likelihood = -324.86, aic = 655.72

arima(y, order = c(1,0,0))

Call:

arima(x = y, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.132 -0.0142

s.e. 0.070 0.1051

sigma^2 estimated as 1.668: log likelihood = -334.99, aic = 675.97

9. High Leverage and High Skewness of 200 Sample Size

arima(x35, order = c(1,0,0))

Call:

arima(x = x35, order = c(1, 0, 0))

Coefficients:

ar1 intercept

0.0138 -0.0425

```
s.e.  0.0320     0.0317
sigma^2 estimated as 0.9514:  log likelihood = -1360.58,  aic = 2727.17

  arima(x30, order = c(1,0,0))
Call:
arima(x = x30, order = c(1, 0, 0))
Coefficients:
         ar1 intercept
      0.0039    -0.0525
s.e.  0.0320     0.0322
sigma^2 estimated as 1.002:  log likelihood = -1385.91,  aic = 2777.82

arima(y, order = c(1,0,0))
Call:
arima(x = y, order = c(1, 0, 0))
Coefficients:
        ar1 intercept
      0.132    -0.0142
s.e.  0.070     0.1051
sigma^2 estimated as 1.668:  log likelihood = -334.99,  aic = 675.97>
```

Appendix H

EGARCH, VAR and MA Computer Output for 200 Simulated Data

1. EGARCH estimation N=200(0.01 low leverage and 0.5 low skewness)

Dependent Variable: Y

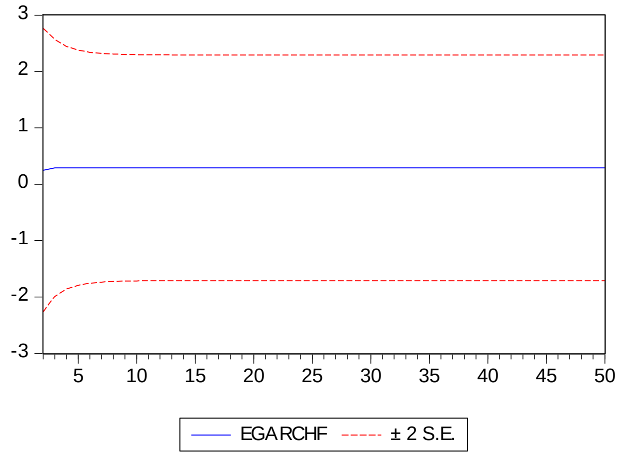
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/15/17 Time: 10:27
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000134	0.062959	-0.002124	0.9983
AR(1)	0.002396	0.073010	0.032815	0.9738
		Variance Equation		
C(3)	-0.651026	0.290762	-2.239035	0.0252
C(4)	0.688630	0.270382	2.546878	0.0109
C(5)	0.071728	0.125992	0.569308	0.5691
C(6)	-0.425210	0.223455	-1.902884	0.0571
T-DIST. DOF	7.354583	3.892371	1.889486	0.0588

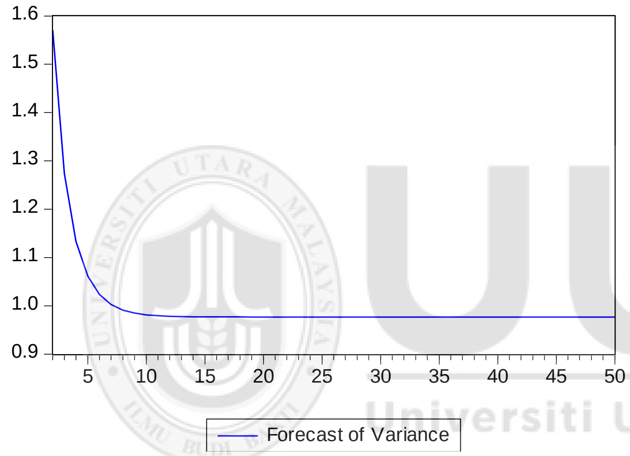
R-squared	-0.005128	Mean dependent var	-0.072121
Adjusted R-squared	-0.010230	S.D. dependent var	1.000000
S.E. of regression	1.005102	Akaike info criterion	2.781458
Sum squared resid	199.0154	Schwarz criterion	2.897303
Log likelihood	-269.7550	Hannan-Quinn criter.	2.828343
Durbin-Watson stat	1.966213		

Inverted AR Roots	.00

2. EGARCH forecast N=200(0.01 low leverage and 0.5 low skewness)



Forecast: EGARCHF	
Actual: D01	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	1.061001
Mean Absolute Error	0.720844
Mean Abs. Percent Error	275.9369
Theil Inequality Coefficient	0.812123
Bias Proportion	0.083719
Variance Proportion	0.906895
Covariance Proportion	0.009386



3. MA estimation N=200(0.01 low leverage and 0.5 low skewness)

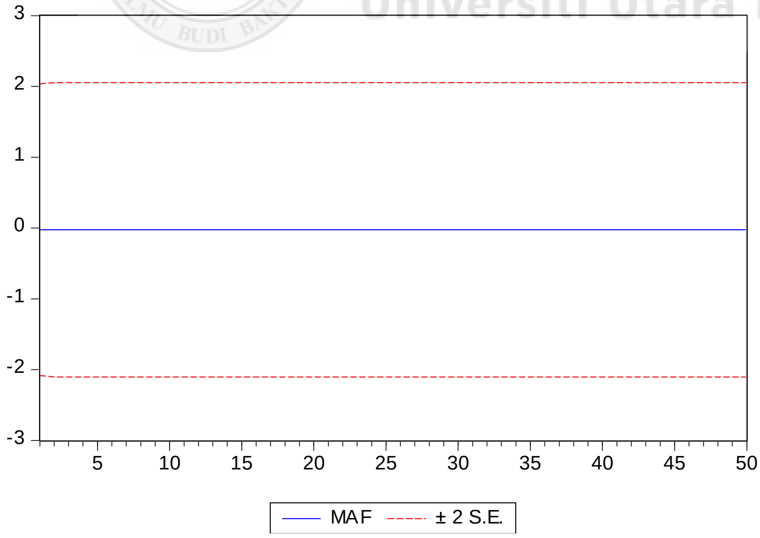
Dependent Variable: Y
Method: Least Squares
Date: 08/15/17 Time: 10:25
Sample: 1 200
Included observations: 200
Convergence achieved after 5 iterations
MA Backcast: 0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.071917	0.071774	-1.001992	0.3176
MA(1)	0.015207	0.071082	0.213932	0.8308

R-squared	0.000192	Mean dependent var	-0.071946
Adjusted R-squared	-0.004858	S.D. dependent var	0.997487
S.E. of regression	0.999907	Akaike info criterion	2.847641
Sum squared resid	197.9632	Schwarz criterion	2.880624
Log likelihood	-282.7641	Hannan-Quinn criter.	2.860989
F-statistic	0.038025	Durbin-Watson stat	2.002003
Prob(F-statistic)	0.845594		

Inverted MA Roots	-.02

4. MA estimation N=200(0.01 low leverage and 0.5 low skewness



Forecast: MAF	
Actual: D01	
Forecast sample: 1 50	
Included observations: 50	
Root Mean Squared Error	1.007804
Mean Absolute Error	0.759568
Mean Abs. Percent Error	110.9657
Theil Inequality Coefficient	0.975212
Bias Proportion	0.000000
Variance Proportion	0.999983
Covariance Proportion	0.000017

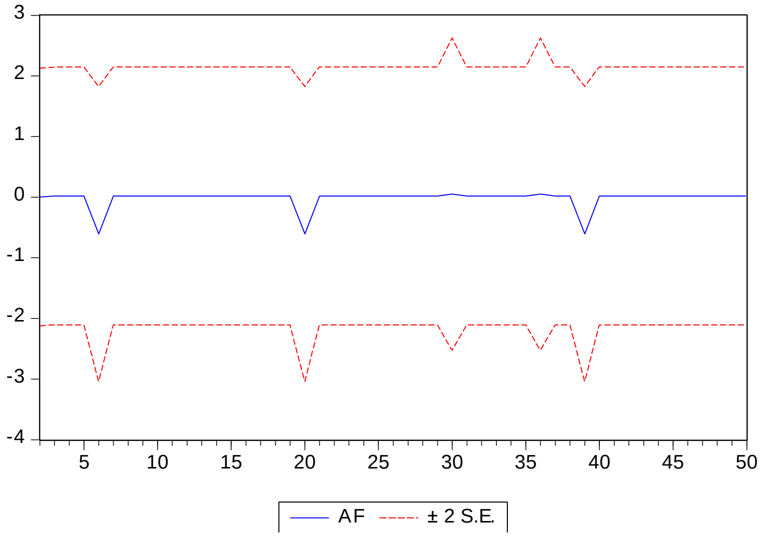
5. VAR estimation N=200(0.01 low leverage and 0.5 low skewness)

Vector Autoregression Estimates
Date: 08/15/17 Time: 10:48
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X15	X26
Y(-1)	0.012751	-0.002319	0.007566
	(0.07160)	(0.00787)	(0.00467)
	[0.17809]	[-0.29468]	[1.62083]
X15(-1)	-0.295836	-0.016021	0.015777
	(0.65122)	(0.07159)	(0.04245)
	[-0.45428]	[-0.22380]	[0.37162]
X26(-1)	-0.034475	0.047702	0.053849
	(1.08989)	(0.11981)	(0.07105)
	[-0.03163]	[0.39815]	[0.75788]
C	-0.074679	-0.014675	0.015034
	(0.07400)	(0.00813)	(0.00482)
	[-1.00914]	[-1.80392]	[3.11615]
R-squared	0.001227	0.001514	0.016719
Adj. R-squared	-0.014139	-0.013847	0.001591
Sum sq. resids	197.7570	2.389742	0.840483
S.E. equation	1.007045	0.110703	0.065652
F-statistic	0.079857	0.098586	1.105182
Log likelihood	-281.7453	157.6321	261.6060
Akaike AIC	2.871812	-1.544041	-2.589005
Schwarz SC	2.938010	-1.477844	-2.522808
Mean dependent	-0.072121	-0.013568	0.015075
S.D. dependent	1.000000	0.109944	0.065704

Determinant resid covariance (dof adj.)	5.35E-05
Determinant resid covariance	5.03E-05
Log likelihood	137.6262
Akaike information criterion	-1.262575
Schwarz criterion	-1.063983

6. VAR estimation N=200(0.01 low leverage and 0.5 low skewness)



Forecast: AF	
Actual: A	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	1.006279
Mean Absolute Error	0.765508
Mean Abs. Percent Error	110.8082
Theil Inequality Coefficient	0.861777
Bias Proportion	0.000000
Variance Proportion	0.741081
Covariance Proportion	0.258919

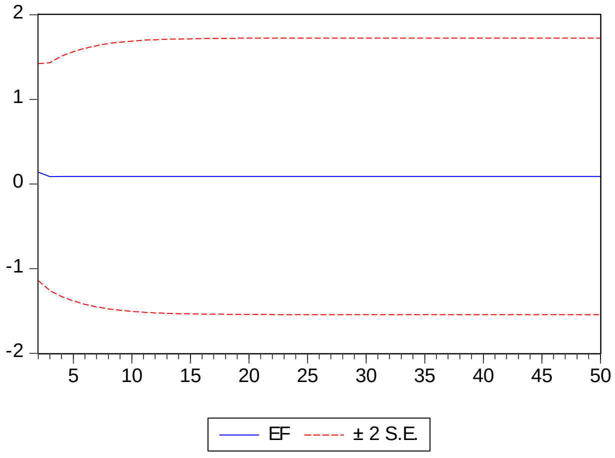
7. EGARCH estimation N=200(0.01 low leverage and 0.7 moderate skew)

Dependent Variable: Y
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/15/17 Time: 12:00
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

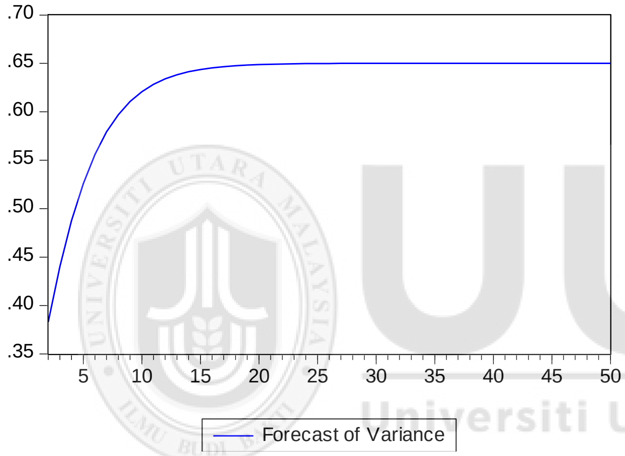
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	-0.000134	0.062959	-0.002124	0.9983
AR(1)	0.002396	0.073010	0.032815	0.9738
Variance Equation				
C(3)	-0.651026	0.290762	-2.239035	0.0252
C(4)	0.688630	0.270382	2.546878	0.0109
C(5)	0.071728	0.125992	0.569308	0.5691
C(6)	-0.425210	0.223455	-1.902884	0.0571
T-DIST. DOF	7.354582	3.892372	1.889486	0.0588

R-squared	-0.005128	Mean dependent var	-0.072121
Adjusted R-squared	-0.010230	S.D. dependent var	1.000000
S.E. of regression	1.005102	Akaike info criterion	2.781458
Sum squared resid	199.0154	Schwarz criterion	2.897303
Log likelihood	-269.7550	Hannan-Quinn criter.	2.828343
Durbin-Watson stat	1.966213		
Inverted AR Roots	.00		

8. EGARCH estimation N=200(0.01 low leverage and 0.7 moderate skewness)



Forecast: EF	
Actual: E	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.817929
Mean Absolute Error	0.643386
Mean Abs. Percent Error	241.2879
Theil Inequality Coefficient	0.894688
Bias Proportion	0.000022
Variance Proportion	0.983621
Covariance Proportion	0.016357



9. MA estimation N=200(0.01 low leverage and 0.7 moderate skewness)

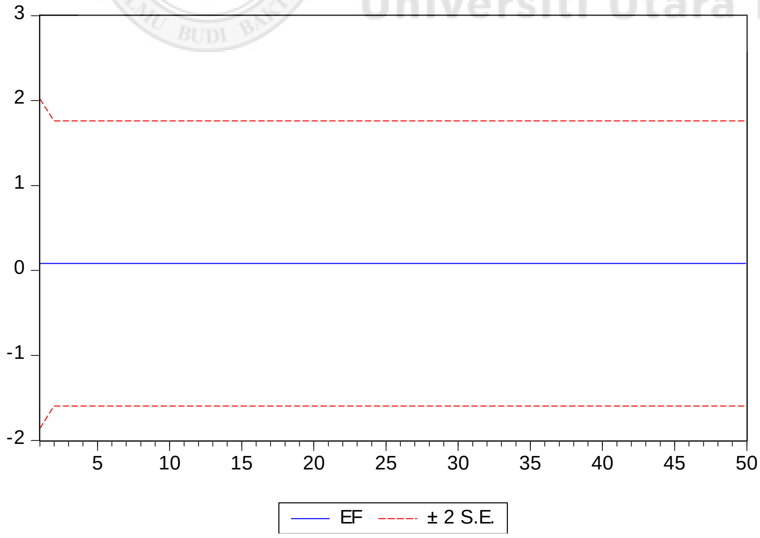
Dependent Variable: Y
Method: Least Squares
Date: 08/15/17 Time: 12:04
Sample: 1 200
Included observations: 200
Convergence achieved after 5 iterations
MA Backcast: 0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.071917	0.071774	-1.001992	0.3176
MA(1)	0.015207	0.071082	0.213932	0.8308

R-squared	0.000192	Mean dependent var	-0.071946
Adjusted R-squared	-0.004858	S.D. dependent var	0.997487
S.E. of regression	1.001224	Akaike info criterion	2.964712
Sum squared resid	197.9632	Schwarz criterion	2.938023
Log likelihood	-293.7614	Hannan-Quinn criter.	2.860989
F-statistic	0.038025	Durbin-Watson stat	2.002003
Prob(F-statistic)	0.845594		

Inverted MA Roots	-.02

10. MA forecast N=200(0.01 low leverage and 0.7 moderate skewness)



Forecast: EF	
Actual: E	
Forecast sample: 1 50	
Included observations: 50	
Root Mean Squared Error	0.814519
Mean Absolute Error	0.642980
Mean Abs. Percent Error	228.9763
Theil Inequality Coefficient	0.902757
Bias Proportion	0.000004
Variance Proportion	0.999232
Covariance Proportion	0.000764

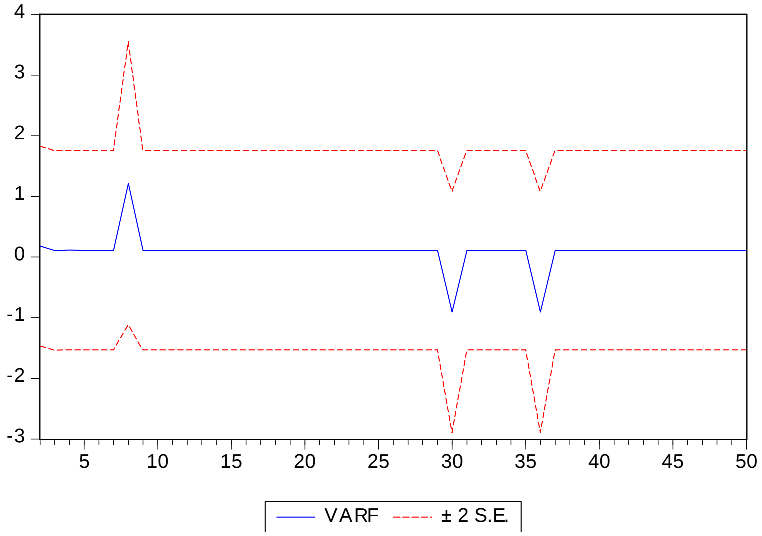
11. VAR estimation N=200(0.01 low leverage and 0.7 moderate skewness)

Vector Autoregression Estimates
Date: 08/15/17 Time: 12:32
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X15	X40
Y(-1)	0.076830	-0.006286	-0.024217
	(0.07300)	(0.00778)	(0.01336)
	[1.05250]	[-0.80789]	[-1.81295]
X15(-1)	0.279240	-0.009248	0.045712
	(0.67450)	(0.07190)	(0.12342)
	[0.41400]	[-0.12862]	[0.37036]
X40(-1)	0.054526	0.013259	0.012550
	(0.39414)	(0.04201)	(0.07212)
	[0.13834]	[0.31559]	[0.17401]
C	0.064551	-0.013498	0.021204
	(0.07464)	(0.00796)	(0.01366)
	[0.86483]	[-1.69655]	[1.55246]
R-squared	0.007633	0.003729	0.016833
Adj. R-squared	-0.007634	-0.011598	0.001708
Sum sq. resids	209.8620	2.384442	7.027122
S.E. equation	1.037408	0.110580	0.189833
F-statistic	0.499965	0.243300	1.112896
Log likelihood	-287.6567	157.8530	50.31222
Akaike AIC	2.931223	-1.546262	-0.465449
Schwarz SC	2.997420	-1.480065	-0.399252
Mean dependent	0.067286	-0.013568	0.019095
S.D. dependent	1.033471	0.109944	0.189995

Determinant resid covariance (dof adj.)	0.000452
Determinant resid covariance	0.000425
Log likelihood	-74.66667
Akaike information criterion	0.871022
Schwarz criterion	1.069613

12. VAR forecast N=200(0.01 low leverage and 0.7 moderate skewness)



Forecast: VARF	
Actual: P	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.780438
Mean Absolute Error	0.587197
Mean Abs. Percent Error	279.4167
Theil Inequality Coefficient	0.709514
Bias Proportion	0.000005
Variance Proportion	0.513424
Covariance Proportion	0.486571

13. EGARCH estimation N=200(0.01 low leverage and 1.2 high skewness)

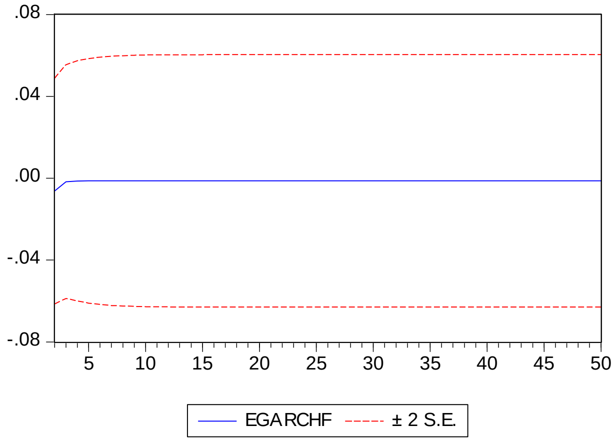
Dependent Variable: Y
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/15/17 Time: 13:51
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Convergence achieved after 36 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000166	0.002246	0.074121	0.9409
AR(1)	0.075662	0.061852	1.223273	0.2212
Variance Equation				
C(3)	-1.695535	0.955355	-1.774770	0.0759
C(4)	-0.281114	0.151754	-1.852437	0.0640
C(5)	0.244701	0.097572	2.507886	0.0121
C(6)	0.725740	0.145519	4.987254	0.0000
T-DIST. DOF	21.06627	32.22258	0.653774	0.5133

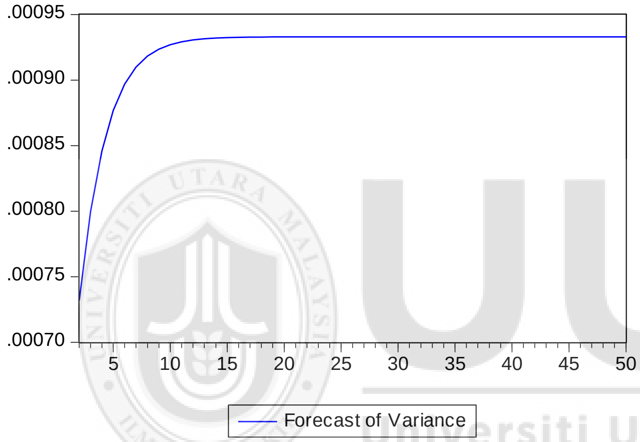
R-squared	-0.002631	Mean dependent var	-0.001434
Adjusted R-squared	-0.007721	S.D. dependent var	0.030628
S.E. of regression	0.030746	Akaike info criterion	-4.151830
Sum squared resid	0.186223	Schwarz criterion	-4.035985
Log likelihood	420.1071	Hannan-Quinn criter.	-4.104945
Durbin-Watson stat	2.026715		

Inverted AR Roots	.08

14. EGARCH forecast N=200(0.01 low leverage and 1.2 high skewness)



Forecast: EGARCHF	
Actual: G	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.035634
Mean Absolute Error	0.027621
Mean Abs. Percent Error	108.7905
Theil Inequality Coefficient	0.956648
Bias Proportion	0.000003
Variance Proportion	0.960584
Covariance Proportion	0.039413



15. MA estimation N=200(0.01 low leverage and 1.2 high skewness)

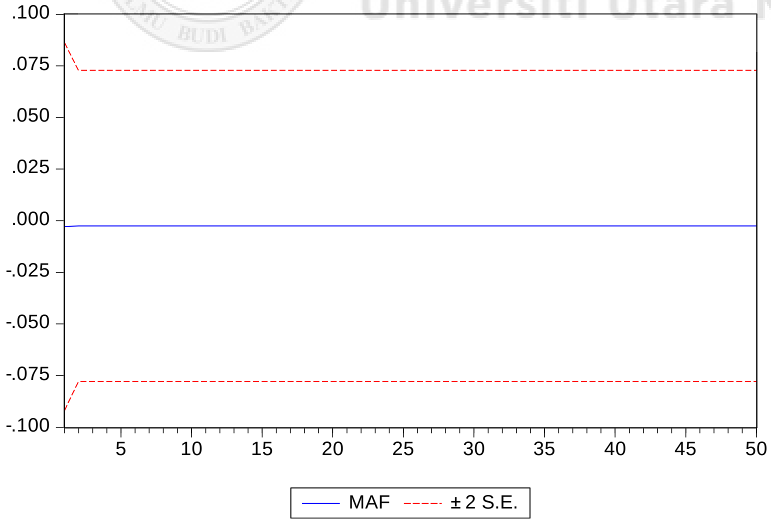
Dependent Variable: Y
Method: Least Squares
Date: 08/15/17 Time: 13:55
Sample: 1 200
Included observations: 200
Convergence achieved after 6 iterations
MA Backcast: 0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001634	0.002257	-0.724188	0.4698
MA(1)	0.039377	0.072363	0.544166	0.5869

R-squared	0.001377	Mean dependent var	-0.001612
Adjusted R-squared	-0.003667	S.D. dependent var	0.030654
S.E. of regression	0.030710	Akaike info criterion	-4.118510
Sum squared resid	0.186734	Schwarz criterion	-4.085527
Log likelihood	413.8510	Hannan-Quinn criter.	-4.105163
F-statistic	0.272943	Durbin-Watson stat	1.961176
Prob(F-statistic)	0.601948		

Inverted MA Roots	-.04

16. MA forecast N=200(0.01 low leverage and 1.2 high skewness)



Forecast: MAF	
Actual: G	
Forecast sample: 1 50	
Included observations: 50	
Root Mean Squared Error	0.036549
Mean Absolute Error	0.028429
Mean Abs. Percent Error	112.5024
Theil Inequality Coefficient	0.932325
Bias Proportion	0.000033
Variance Proportion	0.997941
Covariance Proportion	0.002026

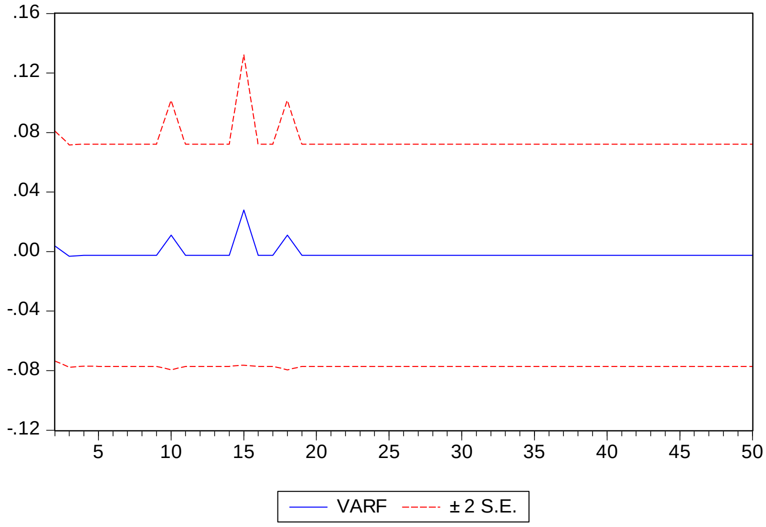
17. VAR estimation N=200(0.01 low leverage and 1.2 high skewness)

Vector Autoregression Estimates
Date: 08/15/17 Time: 15:46
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X1	X13
Y(-1)	0.036652	0.129652	-0.321973
	(0.07260)	(0.95597)	(0.40856)
	[0.50485]	[0.13562]	[-0.78807]
X1(-1)	0.001338	-0.015487	-0.009272
	(0.00544)	(0.07162)	(0.03061)
	[0.24602]	[-0.21624]	[-0.30293]
X13(-1)	0.000220	-0.047227	-0.025913
	(0.01270)	(0.16724)	(0.07147)
	[0.01734]	[-0.28239]	[-0.36256]
C	-0.001317	-0.051668	-0.029205
	(0.00223)	(0.02941)	(0.01257)
	[-0.58968]	[-1.75698]	[-2.32376]
R-squared	0.001588	0.000735	0.004251
Adj. R-squared	-0.013772	-0.014638	-0.011068
Sum sq. resids	0.185440	32.15383	5.872918
S.E. equation	0.030838	0.406068	0.173544
F-statistic	0.103387	0.047833	0.277485
Log likelihood	411.9752	-101.0028	68.16507
Akaike AIC	-4.100253	1.055305	-0.644875
Schwarz SC	-4.034056	1.121502	-0.578678
Mean dependent	-0.001434	-0.049749	-0.027638
S.D. dependent	0.030628	0.403128	0.172592

Determinant resid covariance (dof adj.)	4.72E-06
Determinant resid covariance	4.44E-06
Log likelihood	379.2361
Akaike information criterion	-3.690815
Schwarz criterion	-3.492223

18. VAR forecast N=200(0.01 low leverage and 1.2 high skewness)



Forecast: VARF	
Actual: K	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.035432
Mean Absolute Error	0.027026
Mean Abs. Percent Error	114.1529
Theil Inequality Coefficient	0.867052
Bias Proportion	0.000015
Variance Proportion	0.744255
Covariance Proportion	0.255730

19. EGARCH estimation N=200 (0.05 moderate leverage and 0.5low skewnessness)

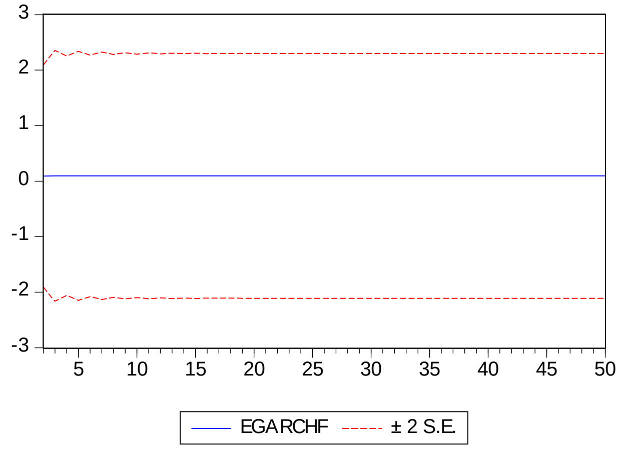
Dependent Variable: Y
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/15/17 Time: 17:38
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Convergence achieved after 26 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1)))
+ C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.042887	0.078677	0.545110	0.5857
AR(1)	-0.077203	0.069344	-1.113333	0.2656
		Variance Equation		
C(3)	-0.131057	0.064260	-2.039459	0.0414
C(4)	0.209730	0.113059	1.855045	0.0636
C(5)	-0.059643	0.078296	-0.761763	0.4462
C(6)	0.960517	0.045534	21.09467	0.0000
T-DIST. DOF	5.123388	1.792701	2.857916	0.0043

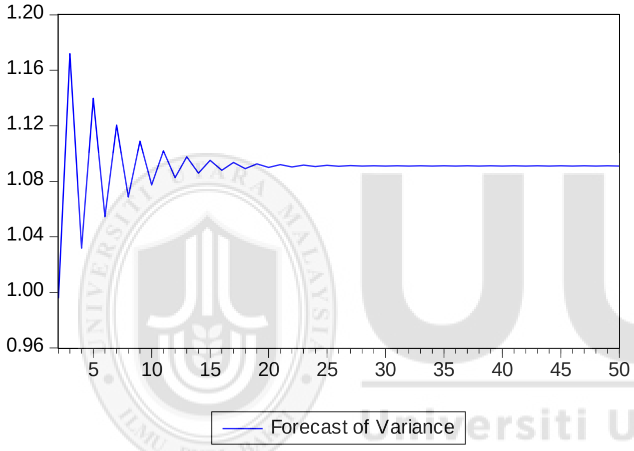
R-squared	0.009150	Mean dependent var	0.020159
Adjusted R-squared	0.004120	S.D. dependent var	1.430806
S.E. of regression	1.427856	Akaike info criterion	3.431959
Sum squared resid	401.6382	Schwarz criterion	3.547804
Log likelihood	-334.4799	Hannan-Quinn criter.	3.478844
Durbin-Watson stat	2.052602		

Inverted AR Roots	-.08

20. EGARCH forecast N=200 (0.05 moderate leverage and 0.5low skewness)



Forecast: EGARCHF	
Actual: A	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	1.225355
Mean Absolute Error	0.907402
Mean Abs. Percent Error	97.75381
Theil Inequality Coefficient	0.929123
Bias Proportion	0.002232
Variance Proportion	0.997028
Covariance Proportion	0.000739



21. MA ESTIMATION N=200 (0.05 moderate leverage and 0.5 low skewness)

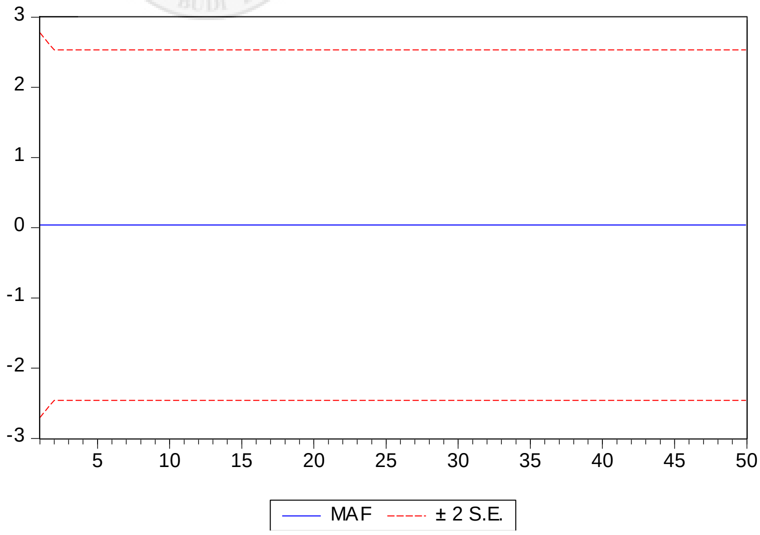
Dependent Variable: Y
Method: Least Squares
Date: 08/15/17 Time: 17:43
Sample: 1 200
Included observations: 200
Convergence achieved after 7 iterations
MA Backcast: 0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.016384	0.088393	0.185355	0.8531
MA(1)	-0.122339	0.070562	-1.733789	0.0845

R-squared	0.011957	Mean dependent var	0.016314
Adjusted R-squared	0.006967	S.D. dependent var	1.428243
S.E. of regression	1.423259	Akaike info criterion	3.553725
Sum squared resid	401.0817	Schwarz criterion	3.586708
Log likelihood	-353.3725	Hannan-Quinn criter.	3.567073
F-statistic	2.396124	Durbin-Watson stat	1.973783
Prob(F-statistic)	0.123233		

Inverted MA Roots	.12

22. MA forecast N=200 (0.05 moderate leverage and 0.5 low skewness)



Forecast: MAF	
Actual: A	
Forecast sample: 1 50	
Included observations: 50	
Root Mean Squared Error	1.211821
Mean Absolute Error	0.895799
Mean Abs. Percent Error	96.24596
Theil Inequality Coefficient	0.969925
Bias Proportion	0.000000
Variance Proportion	0.999987
Covariance Proportion	0.000012

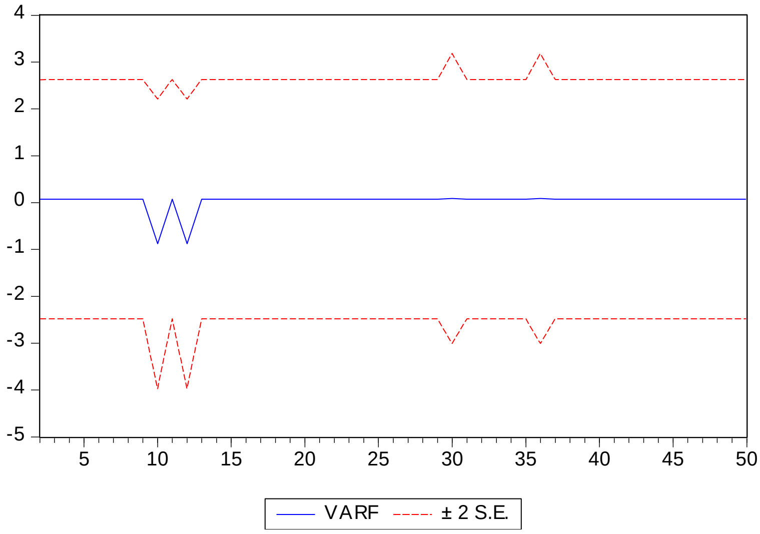
23. VAR estimation N=200 (0.05 moderate leverage and 0.5 low skewness)

Vector Autoregression Estimates
Date: 08/15/17 Time: 18:01
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X15	X30
Y(-1)	-0.096363	0.000771	0.003290
	(0.07151)	(0.00553)	(0.00733)
	[-1.34758]	[0.13935]	[0.44891]
X15(-1)	-0.907070	-0.016690	0.034672
	(0.92724)	(0.07175)	(0.09502)
	[-0.97825]	[-0.23261]	[0.36488]
X30(-1)	-0.091227	0.021311	-0.045206
	(0.70050)	(0.05420)	(0.07179)
	[-0.13023]	[0.39317]	[-0.62972]
C	0.011936	-0.014479	0.033519
	(0.10471)	(0.00810)	(0.01073)
	[0.11399]	[-1.78698]	[3.12372]
R-squared	0.014939	0.001082	0.004069
Adj. R-squared	-0.000216	-0.014286	-0.011253
Sum sq. resids	399.2914	2.390778	4.193420
S.E. equation	1.430961	0.110727	0.146645
F-statistic	0.985776	0.070386	0.265560
Log likelihood	-351.6592	157.5890	101.6801
Akaike AIC	3.574465	-1.543608	-0.981710
Schwarz SC	3.640662	-1.477411	-0.915513
Mean dependent	0.020159	-0.013568	0.031658
S.D. dependent	1.430806	0.109944	0.145827

Determinant resid covariance (dof adj.)	0.000533
Determinant resid covariance	0.000502
Log likelihood	-91.14510
Akaike information criterion	1.036634
Schwarz criterion	1.235225

24. VAR forecast N=200 (0.05 moderate leverage and 0.5 low skewness)



Forecast: VARF	
Actual: S	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	1.211501
Mean Absolute Error	0.875070
Mean Abs. Percent Error	92.30211
Theil Inequality Coefficient	0.855060
Bias Proportion	0.000001
Variance Proportion	0.730045
Covariance Proportion	0.269955

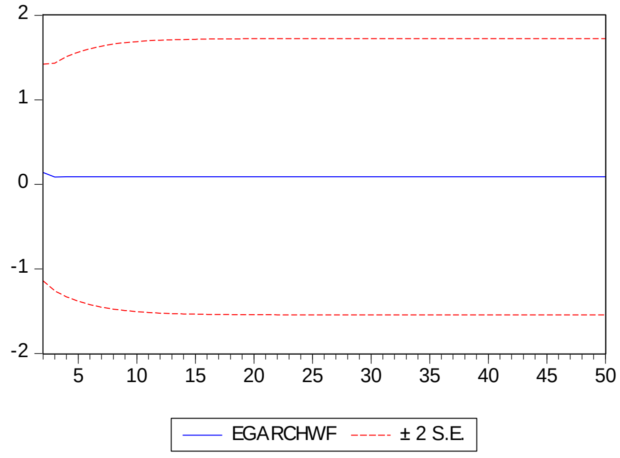
25. EGARCH estimation N=200(0.05 moderate leverage and 0.7moderate skewness)

Dependent Variable: Y
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/13/17 Time: 08:53
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1)))
+ C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

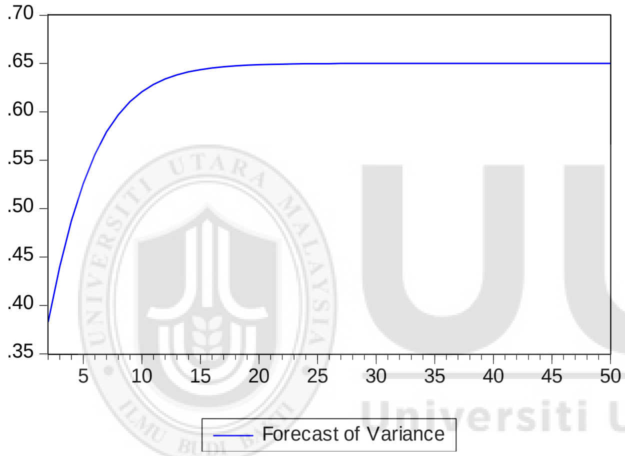
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.059694	0.081798	0.729773	0.4655
AR(1)	0.112505	0.079966	1.406908	0.1595
Variance Equation				
C(3)	-0.189064	0.211801	-0.892650	0.3720
C(4)	0.193144	0.171285	1.127612	0.2595
C(5)	-0.375537	0.104848	-3.581735	0.0003
C(6)	-0.235592	0.221063	-1.065719	0.2866
T-DIST. DOF	335.2047	11955.46	0.028038	0.9776

R-squared	0.005690	Mean dependent var	0.067286
Adjusted R-squared	0.000642	S.D. dependent var	1.033471
S.E. of regression	1.033139	Akaike info criterion	2.877968
Sum squared resid	210.2730	Schwarz criterion	2.993813
Log likelihood	-279.3579	Hannan-Quinn criter.	2.924854
Durbin-Watson stat	2.060796		
Inverted AR Roots	.11		

26. EGARCH forecast N=200 (0.05 moderate leverage and 0.7 moderate skewness)



Forecast: EGARCHWF	
Actual: W	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.817929
Mean Absolute Error	0.643386
Mean Abs. Percent Error	241.2879
Theil Inequality Coefficient	0.894688
Bias Proportion	0.000022
Variance Proportion	0.983621
Covariance Proportion	0.016357



27. MA estimation N=200(0.05 moderate leverage and 0.7 moderate skewness)

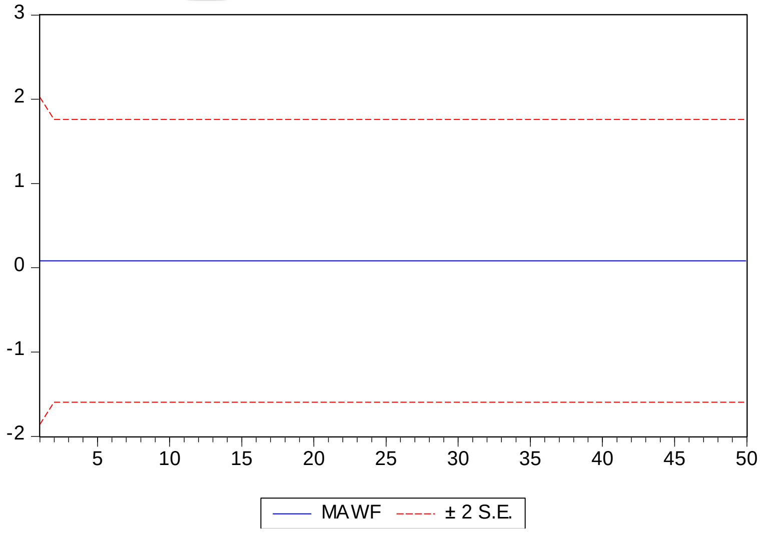
Dependent Variable: Y
Method: Least Squares
Date: 08/13/17 Time: 09:25
Sample: 1 200
Included observations: 200
Convergence achieved after 4 iterations
MA Backcast: 0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.066745	0.078613	0.849032	0.3969
MA(1)	0.079587	0.071083	1.119625	0.2642

R-squared	0.006429	Mean dependent var	0.067154
Adjusted R-squared	0.001411	S.D. dependent var	1.030872
S.E. of regression	1.030145	Akaike info criterion	2.907225
Sum squared resid	210.1173	Schwarz criterion	2.940209
Log likelihood	-288.7225	Hannan-Quinn criter.	2.920573
F-statistic	1.281215	Durbin-Watson stat	1.993045
Prob(F-statistic)	0.259042		

Inverted MA Roots	-.08

28. MA forecast N=200 (0.05 moderate leverage and 0.7 moderate skewness)



Forecast: MAWF
Actual: W
Forecast sample: 1 50
Included observations: 50

Root Mean Squared Error	0.814555
Mean Absolute Error	0.643030
Mean Abs. Percent Error	228.9860
Theil Inequality Coefficient	0.902748
Bias Proportion	0.000005
Variance Proportion	0.999995
Covariance Proportion	0.000000

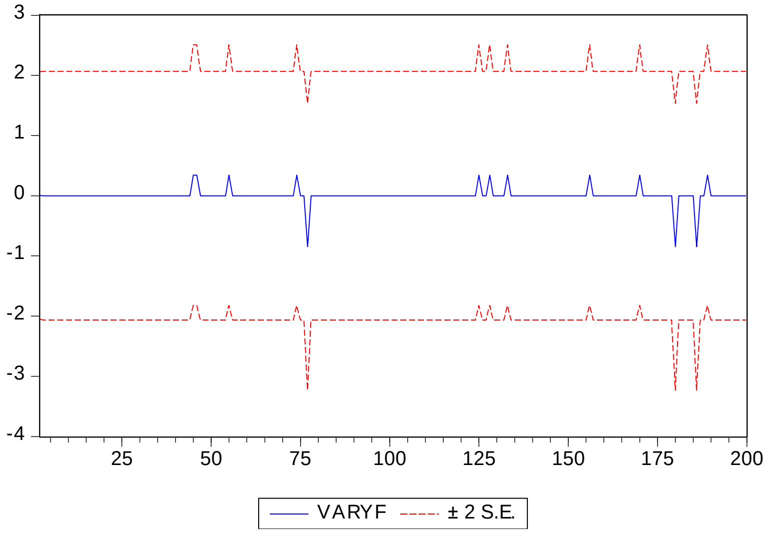
29. VAR estimation N=200(0.05 moderate leverage and 0.7 moderate skewness)

Vector Autoregression Estimates
Date: 08/13/17 Time: 09:38
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X15	X26
Y(-1)	0.075080	-0.006080	-0.000514
	(0.07192)	(0.00767)	(0.00459)
	[1.04398]	[-0.79224]	[-0.11205]
X15(-1)	0.267607	-0.010096	0.016639
	(0.67367)	(0.07189)	(0.04298)
	[0.39724]	[-0.14044]	[0.38714]
X26(-1)	0.856890	0.054471	0.052127
	(1.12323)	(0.11987)	(0.07166)
	[0.76288]	[0.45443]	[0.72742]
C	0.052642	-0.014092	0.014552
	(0.07612)	(0.00812)	(0.00486)
	[0.69154]	[-1.73473]	[2.99637]
R-squared	0.010489	0.004275	0.003536
Adj. R-squared	-0.004734	-0.011044	-0.011794
Sum sq. resids	209.2580	2.383136	0.851752
S.E. equation	1.035914	0.110550	0.066091
F-statistic	0.689007	0.279050	0.230638
Log likelihood	-287.3700	157.9076	260.2809
Akaike AIC	2.928341	-1.546810	-2.575687
Schwarz SC	2.994538	-1.480612	-2.509490
Mean dependent	0.067286	-0.013568	0.015075
S.D. dependent	1.033471	0.109944	0.065704

Determinant resid covariance (dof adj.)	5.63E-05
Determinant resid covariance	5.30E-05
Log likelihood	132.5011
Akaike information criterion	-1.211067
Schwarz criterion	-1.012475

30. VAR forecast N=200(0.05 moderate leverage and 0.7 moderate skewness)



Forecast: VARYF	
Actual: Y	
Forecast sample: 1 200	
Adjusted sample: 2 200	
Included observations: 199	
Root Mean Squared Error	1.024781
Mean Absolute Error	0.777904
Mean Abs. Percent Error	96.17985
Theil Inequality Coefficient	0.881693
Bias Proportion	0.003763
Variance Proportion	0.774255
Covariance Proportion	0.221982

31. EGARCH estimation N=200(0.05 moderate leverage and 1.2 high skewness)

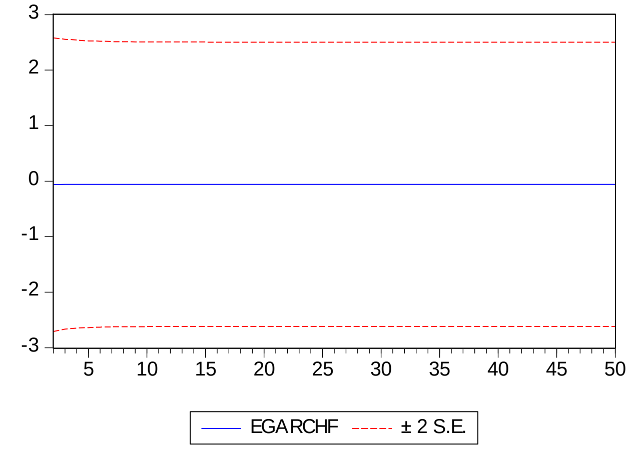
Dependent Variable: Y
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/15/17 Time: 20:28
Sample (adjusted): 2 198
Included observations: 197 after adjustments
Convergence achieved after 24 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1)))
+ C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.039898	0.080255	0.497144	0.6191
AR(1)	-0.053838	0.076905	-0.700062	0.4839
		Variance Equation		
C(3)	-0.116174	0.180892	-0.642231	0.5207
C(4)	0.470653	0.239169	1.967872	0.0491
C(5)	-0.302460	0.138965	-2.176517	0.0295
C(6)	0.478044	0.307003	1.557132	0.1194
T-DIST. DOF	6.667645	3.488071	1.911556	0.0559

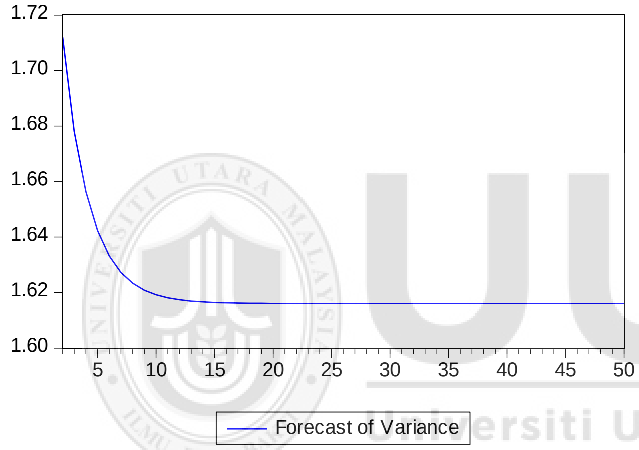
R-squared	-0.000733	Mean dependent var	0.137013
Adjusted R-squared	-0.005865	S.D. dependent var	1.293745
S.E. of regression	1.297533	Akaike info criterion	3.291818
Sum squared resid	328.3006	Schwarz criterion	3.408480
Log likelihood	-317.2440	Hannan-Quinn criter.	3.339039
Durbin-Watson stat	2.043412		

Inverted AR Roots	-.05

32. EGARCH Forecast N=200 (0.05 moderate leverage and 1.2 high skewness)



Forecast: EGARCHF	
Actual: B	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 48	
Root Mean Squared Error	1.310817
Mean Absolute Error	0.956724
Mean Abs. Percent Error	118.4882
Theil Inequality Coefficient	0.957897
Bias Proportion	0.000056
Variance Proportion	0.998823
Covariance Proportion	0.001122



33. MA estimation N=200(0.05 moderate leverage and 1.2 high skewness)

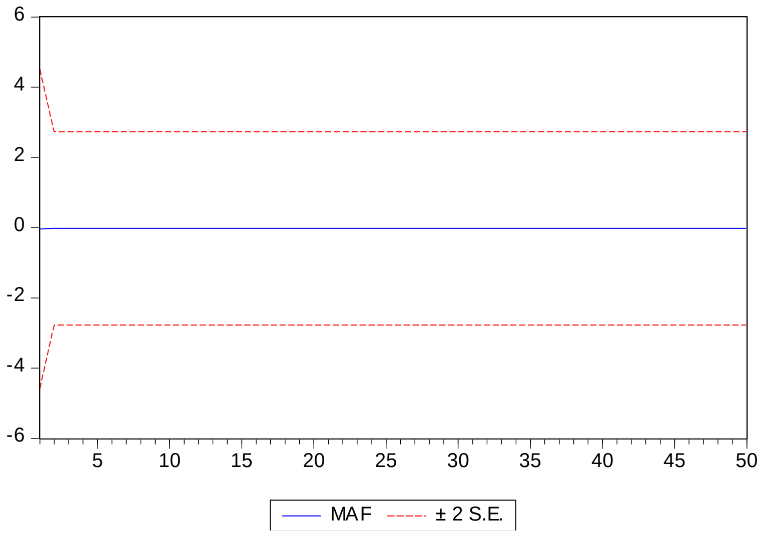
Dependent Variable: Y
Method: Least Squares
Date: 08/15/17 Time: 20:31
Sample (adjusted): 3 198
Included observations: 196 after adjustments
Convergence achieved after 5 iterations
MA Backcast: 2
Instrument specification: C
Lagged dependent variable & regressors added to instrument list

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.138510	0.084129	1.646390	0.1013
MA(1)	-0.091104	0.071729	-1.270117	0.2056

R-squared	0.007652	Mean dependent var	0.138906
Adjusted R-squared	0.002537	S.D. dependent var	1.296784
S.E. of regression	1.295138	Akaike info criteria	3.445014
Sum squared resid	325.4123	Schwarz criteria	3.494603
Log likelihood	-339.7712	Hannan-Quinn criter.	0.728171
F-statistic	0.728171	Durbin-Watson stat	1.986564
Prob(F-statistic)	0.393477		

Inverted MA Roots	.09

34. MA Forecast N=200(0.05 moderate leverage and 1.2 high skewness)



Forecast: MAF	
Actual: B	
Forecast sample: 1 50	
Included observations: 49	
Root Mean Squared Error	1.301238
Mean Absolute Error	0.948659
Mean Abs. Percent Error	103.4675
Theil Inequality Coefficient	0.983480
Bias Proportion	0.000922
Variance Proportion	0.996204
Covariance Proportion	0.002874

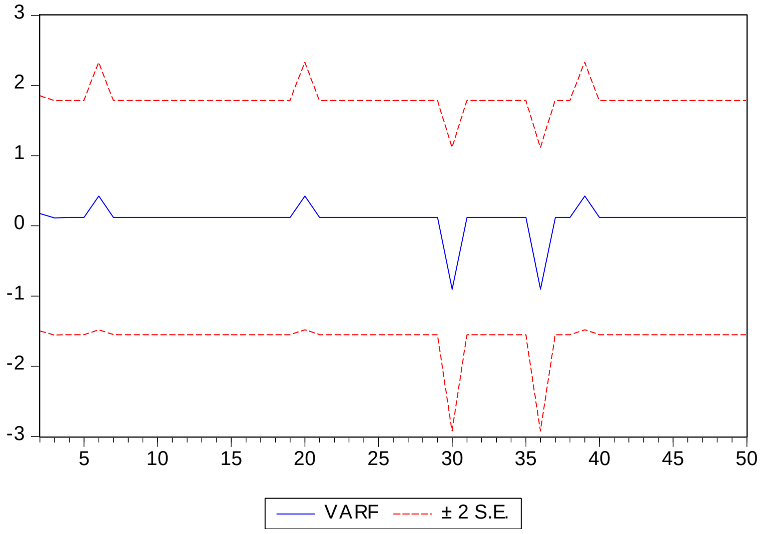
35. VAR estimationN=200(0.05 moderate leverage and 1.2 high skewness)

Vector Autoregression Estimates
Date: 08/15/17 Time: 18:01
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X15	X30
Y(-1)	-0.096363	0.000771	0.003290
	(0.07151)	(0.00553)	(0.00733)
	[-1.34758]	[0.13935]	[0.44891]
X15(-1)	-0.907070	-0.016690	0.034672
	(0.92724)	(0.07175)	(0.09502)
	[-0.97825]	[-0.23261]	[0.36488]
X30(-1)	-0.091227	0.021311	-0.045206
	(0.70050)	(0.05420)	(0.07179)
	[-0.13023]	[0.39317]	[-0.62972]
C	0.011936	-0.014479	0.033519
	(0.10471)	(0.00810)	(0.01073)
	[0.11399]	[-1.78698]	[3.12372]
R-squared	0.014939	0.001082	0.004069
Adj. R-squared	-0.000216	-0.014286	-0.011253
Sum sq. resids	399.2914	2.390778	4.193420
S.E. equation	1.430961	0.110727	0.146645
F-statistic	0.985776	0.070386	0.265560
Log likelihood	-351.6592	157.5890	101.6801
Akaike AIC	3.574465	-1.543608	-0.981710
Schwarz SC	3.640662	-1.477411	-0.915513
Mean dependent	0.020159	-0.013568	0.031658
S.D. dependent	1.430806	0.109944	0.145827

Determinant resid covariance (dof adj.)	0.000533
Determinant resid covariance	0.000502
Log likelihood	-91.14510
Akaike information criterion	1.036634
Schwarz criterion	1.235225

36. VAR forecast N=200(0.05 moderate leverage and 1.2 high skewness



Forecast: VARF	
Actual: P	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.791565
Mean Absolute Error	0.598730
Mean Abs. Percent Error	287.5479
Theil Inequality Coefficient	0.745013
Bias Proportion	0.000004
Variance Proportion	0.573649
Covariance Proportion	0.426347

37. GARCH estimation N=200(0.09 high leverage and 0.5 low skewness)

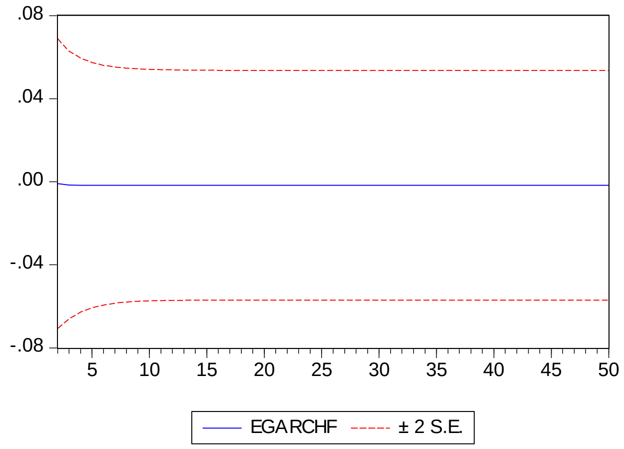
Dependent Variable: Y
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/16/17 Time: 07:05
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Convergence achieved after 50 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.000364	0.002049	0.177405	0.8592
AR(1)	0.100261	0.051974	1.929076	0.0537
Variance Equation				
C(3)	-1.695209	0.857571	-1.976758	0.0481
C(4)	-0.364154	0.140392	-2.593830	0.0095
C(5)	0.228315	0.095214	2.397912	0.0165
C(6)	0.724207	0.127756	5.668674	0.0000
T-DIST. DOF	20.13125	28.31180	0.711055	0.4771

R-squared	-0.000624	Mean dependent var	-0.001484
Adjusted R-squared	-0.005704	S.D. dependent var	0.027825
S.E. of regression	0.027905	Akaike info criterion	-4.350280
Sum squared resid	0.153396	Schwarz criterion	-4.234435
Log likelihood	439.8529	Hannan-Quinn criter.	-4.303395
Durbin-Watson stat	2.011708		

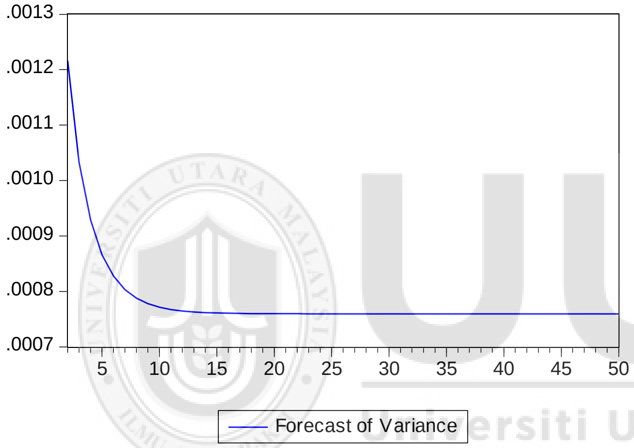
Inverted AR Roots	.10

38. GARCH forecast N=200(0.09 high leverage and 0.5 low skewness)



Forecast: EGARCHF
Actual: Z
Forecast sample: 1 50
Adjusted sample: 2 50
Included observations: 49

Root Mean Squared Error	0.031946
Mean Absolute Error	0.024493
Mean Abs. Percent Error	119.6734
Theil Inequality Coefficient	0.949640
Bias Proportion	0.000031
Variance Proportion	0.990683
Covariance Proportion	0.009287



39. MA estimationN=200(0.09 high leverage and 0.5 low skewness)

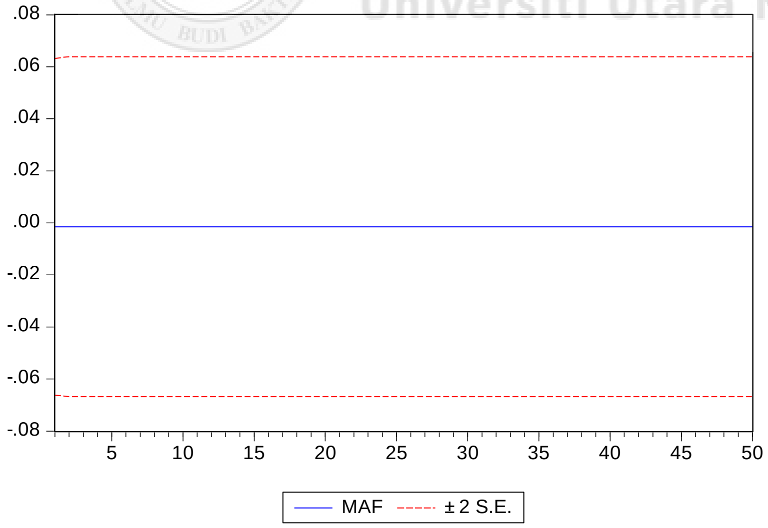
Dependent Variable: Y
Method: Least Squares
Date: 08/16/17   Time: 07:07
Sample: 1 200
Included observations: 200
Convergence achieved after 6 iterations
MA Backcast: 0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.001682	0.002113	-0.795687	0.4272
MA(1)	0.073305	0.072104	1.016669	0.3106

R-squared	0.004641	Mean dependent var	-0.001644
Adjusted R-squared	-0.000386	S.D. dependent var	0.027847
S.E. of regression	0.027853	Akaike info criterion	-4.313832
Sum squared resid	0.153602	Schwarz criterion	-4.280849
Log likelihood	433.3832	Hannan-Quinn criter.	-4.300485
F-statistic	0.923289	Durbin-Watson stat	1.966967
Prob(F-statistic)	0.337785		

Inverted MA Roots	-.07

40. MA forecast N=200(0.09 high leverage and 0.5 low skewness)



Forecast: MAF
Actual: Z
Forecast sample: 1 50
Included observations: 50

Root Mean Squared Error	0.031678
Mean Absolute Error	0.024308
Mean Abs. Percent Error	116.9023
Theil Inequality Coefficient	0.953415
Bias Proportion	0.000000
Variance Proportion	0.999954
Covariance Proportion	0.000046

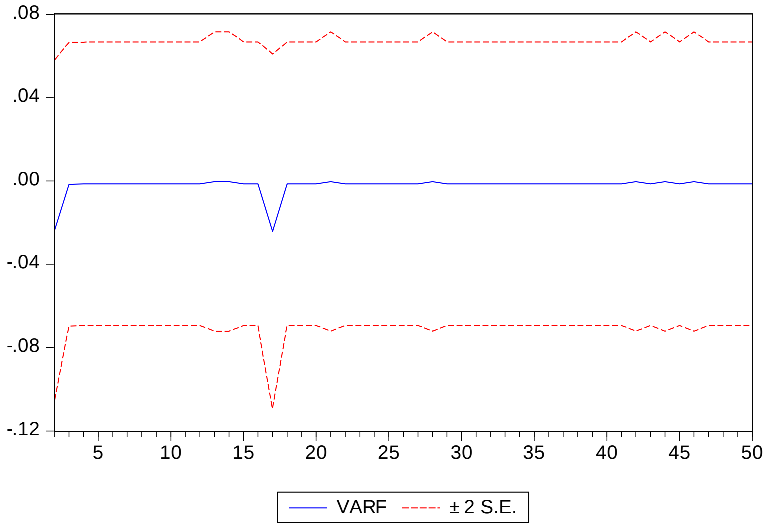
41. VAR estimation N=200(0.09 high leverage and 0.5 low skewness)

Vector Autoregression Estimates
Date: 08/16/17 Time: 07:32
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X23	X28
Y(-1)	0.066716	-0.046404	0.393600
	(0.07254)	(0.06841)	(0.21978)
	[0.91970]	[-0.67835]	[1.79087]
X23(-1)	0.041009	0.131080	0.190500
	(0.07520)	(0.07092)	(0.22785)
	[0.54530]	[1.84829]	[0.83607]
X28(-1)	-0.000226	0.015224	-0.043920
	(0.02344)	(0.02211)	(0.07103)
	[-0.00962]	[0.68862]	[-0.61836]
C	-0.001086	-0.006854	0.018723
	(0.00210)	(0.00198)	(0.00638)
	[-0.51622]	[-3.45349]	[2.93660]
R-squared	0.005724	0.022677	0.020568
Adj. R-squared	-0.009572	0.007642	0.005499
Sum sq. resids	0.152423	0.135548	1.399161
S.E. equation	0.027958	0.026365	0.084706
F-statistic	0.374228	1.508229	1.364973
Log likelihood	431.4840	443.1586	210.8957
Akaike AIC	-4.296322	-4.413654	-2.079354
Schwarz SC	-4.230125	-4.347457	-2.013157
Mean dependent	-0.001484	-0.007538	0.016080
S.D. dependent	0.027825	0.026466	0.084940

Determinant resid covariance (dof adj.)	3.88E-09
Determinant resid covariance	3.65E-09
Log likelihood	431.48
Akaike information criterion	-0.7956
Schwarz criterion	-0.5974

42. MA estimation N=200(0.09 high leverage and 0.5 low skewness)



Forecast: VARF	
Actual: U	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.032216
Mean Absolute Error	0.024667
Mean Abs. Percent Error	142.3351
Theil Inequality Coefficient	0.859572
Bias Proportion	0.000010
Variance Proportion	0.750625
Covariance Proportion	0.249365

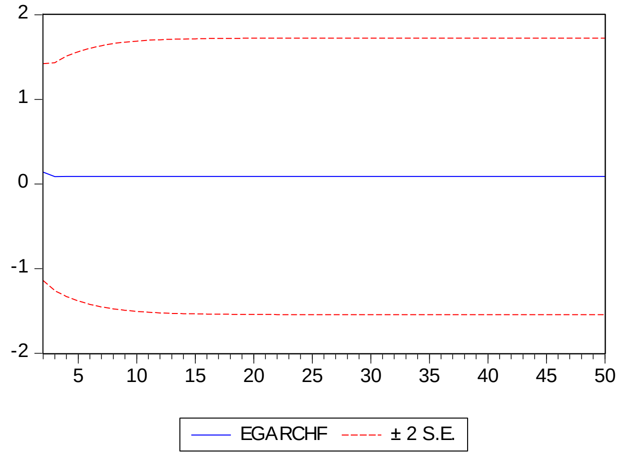
43. GARCH estimation N=200(0.09 high leverage and 0.5 low skewness)

Dependent Variable: Y
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/16/17 Time: 08:36
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Convergence achieved after 14 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

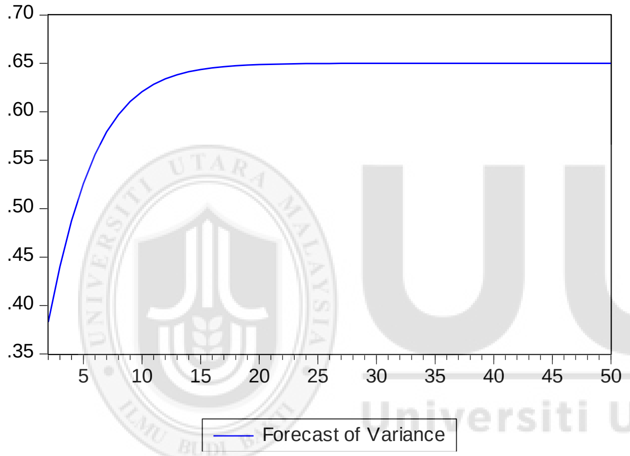
Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.059694	0.081798	0.729775	0.4655
AR(1)	0.112505	0.079966	1.406903	0.1595
Variance Equation				
C(3)	-0.189063	0.211803	-0.892639	0.3721
C(4)	0.193143	0.171286	1.127604	0.2595
C(5)	-0.375537	0.104848	-3.581717	0.0003
C(6)	-0.235592	0.221064	-1.065715	0.2866
T-DIST. DOF	334.9883	11940.08	0.028056	0.9776

R-squared	0.005690	Mean dependent var	0.067286
Adjusted R-squared	0.000642	S.D. dependent var	1.033471
S.E. of regression	1.033139	Akaike info criterion	2.877969
Sum squared resid	210.2730	Schwarz criterion	2.993813
Log likelihood	-279.3579	Hannan-Quinn criter.	2.924854
Durbin-Watson stat	2.060795		
Inverted AR Roots	.11		

44. EGARCH forecast N=200(0.09 high leverage and 0.7 moderate skewness)



Forecast: EGARCHF	
Actual: A	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.817929
Mean Absolute Error	0.643386
Mean Abs. Percent Error	241.2879
Theil Inequality Coefficient	0.894688
Bias Proportion	0.000022
Variance Proportion	0.983621
Covariance Proportion	0.016357



45. MA estimation N=200 (0.09 high leverage and 0.7 moderate skewness)

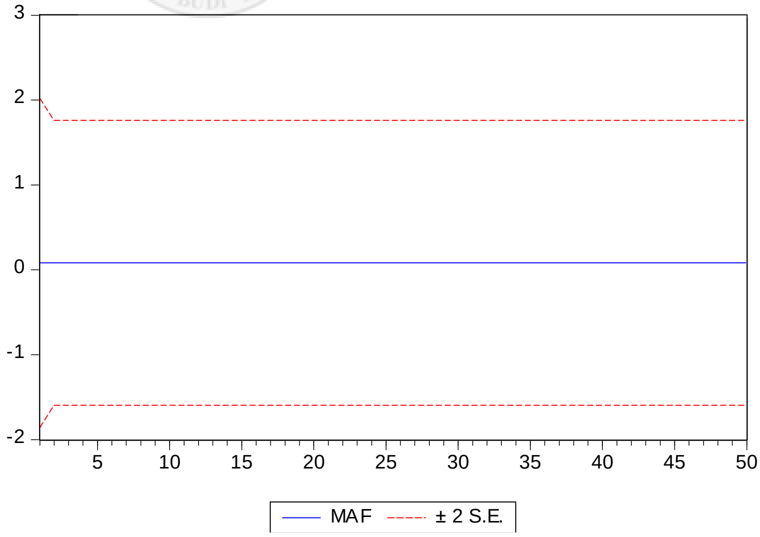
Dependent Variable: Y
Method: Least Squares
Date: 08/16/17 Time: 08:44
Sample: 1 200
Included observations: 200
Convergence achieved after 4 iterations
MA Backcast: 0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.066745	0.078613	0.849032	0.3969
MA(1)	0.079587	0.071083	1.119625	0.2642

R-squared	0.006429	Mean dependent var	0.067154
Adjusted R-squared	0.001411	S.D. dependent var	1.030872
S.E. of regression	1.030145	Akaike info criterion	2.907225
Sum squared resid	210.1173	Schwarz criterion	2.940209
Log likelihood	-288.7225	Hannan-Quinn criter.	2.920573
F-statistic	1.281215	Durbin-Watson stat	1.993045
Prob(F-statistic)	0.259042		

Inverted MA Roots	-.08

46. MA forecast N=200(0.09 high leverage and 0.7 moderate skewness)



Forecast: MAF	
Actual: A	
Forecast sample: 1 50	
Included observations: 50	
Root Mean Squared Error	0.814519
Mean Absolute Error	0.642980
Mean Abs. Percent Error	228.9763
Theil Inequality Coefficient	0.902757
Bias Proportion	0.000004
Variance Proportion	0.999232
Covariance Proportion	0.000764

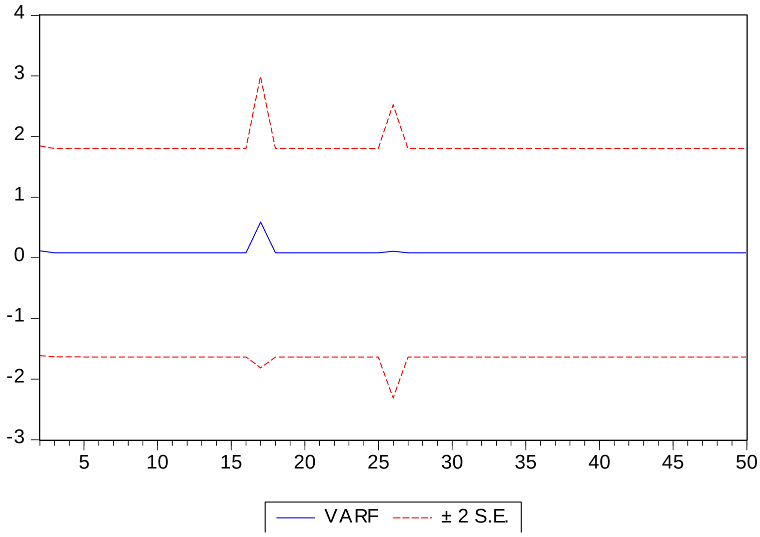
47. VAR estimation N=200 (0.09 high leverage and 0.7 moderate skewness)

Vector Autoregression Estimates
Date: 08/16/17 Time: 09:03
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X28	X33
Y(-1)	0.061035	0.001933	-0.000611
	(0.07120)	(0.00492)	(0.00985)
	[0.85728]	[0.39286]	[-0.06206]
X28(-1)	1.694881	-0.023155	-0.041185
	(1.03855)	(0.07179)	(0.14363)
	[1.63196]	[-0.32254]	[-0.28674]
X33(-1)	0.831829	-0.011992	-0.020462
	(0.52070)	(0.03599)	(0.07201)
	[1.59752]	[-0.33319]	[-0.28414]
C	0.029177	0.010386	0.020969
	(0.07421)	(0.00513)	(0.01026)
	[0.39317]	[2.02472]	[2.04315]
R-squared	0.031837	0.001649	0.000879
Adj. R-squared	0.016942	-0.013710	-0.014492
Sum sq. resids	204.7434	0.978283	3.916153
S.E. equation	1.024679	0.070830	0.141714
F-statistic	2.137472	0.107384	0.057179
Log likelihood	-285.1998	246.4997	108.4866
Akaike AIC	2.906531	-2.437183	-1.050117
Schwarz SC	2.972728	-2.370986	-0.983920
Mean dependent	0.067286	0.010050	0.020101
S.D. dependent	1.033471	0.070349	0.140698

Determinant resid covariance (dof adj.)	0.000104
Determinant resid covariance	9.75E-05
Log likelihood	71.81507
Akaike information criterion	-0.601156
Schwarz criterion	-0.402565

48. VAR forecast N=200 (0.09 high leverage and 0.7 moderate skewness)



Forecast: VARF	
Actual: P	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	0.815445
Mean Absolute Error	0.635168
Mean Abs. Percent Error	229.9929
Theil Inequality Coefficient	0.865169
Bias Proportion	0.000001
Variance Proportion	0.839008
Covariance Proportion	0.160991

49. EGARCH estimation N=200 (0.09 high leverage and 1.2 high skewness)

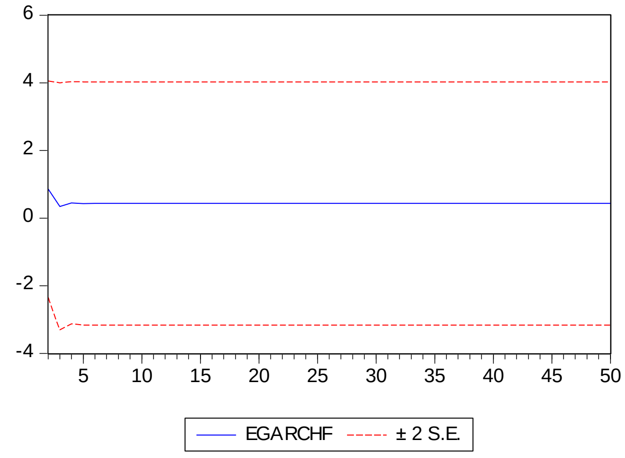
Dependent Variable: Y
Method: ML - ARCH (Marquardt) - Student's t distribution
Date: 08/16/17 Time: 09:24
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Convergence achieved after 17 iterations
Presample variance: backcast (parameter = 0.7)
LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) + C(5)
*RESID(-1)/@SQRT(GARCH(-1)) + C(6)*LOG(GARCH(-1))

Variable	Coefficient	Std. Error	z-Statistic	Prob.
C	0.020993	0.092883	0.226011	0.8212
AR(1)	-0.099867	0.075201	-1.328010	0.1842
Variance Equation				
C(3)	-0.051734	0.071413	-0.724428	0.4688
C(4)	0.142972	0.114151	1.252477	0.2104
C(5)	-0.001957	0.077030	-0.025411	0.9797
C(6)	0.923481	0.110526	8.355313	0.0000
T-DIST. DOF	7.895627	5.181577	1.523788	0.1276

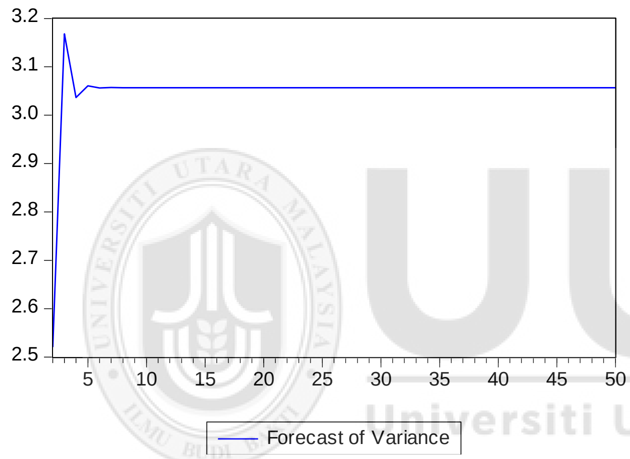
R-squared	0.010973	Mean dependent var	0.029784
Adjusted R-squared	0.005953	S.D. dependent var	1.502179
S.E. of regression	1.497701	Akaike info criterion	3.620747
Sum squared resid	441.8925	Schwarz criterion	3.736592
Log likelihood	-353.2643	Hannan-Quinn criter.	3.667632
Durbin-Watson stat	2.021259		

Inverted AR Roots	-.10

50. EGARCH forecast N=200 (0.09 high leverage and 1.2 high skewness)



Forecast: EGARCHF	
Actual: B	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	1.795642
Mean Absolute Error	1.265990
Mean Abs. Percent Error	381.1213
Theil Inequality Coefficient	0.791686
Bias Proportion	0.004807
Variance Proportion	0.935559
Covariance Proportion	0.059634



51. MA estimation N=200 (0.09 high leverage and 1.2 high skewness)

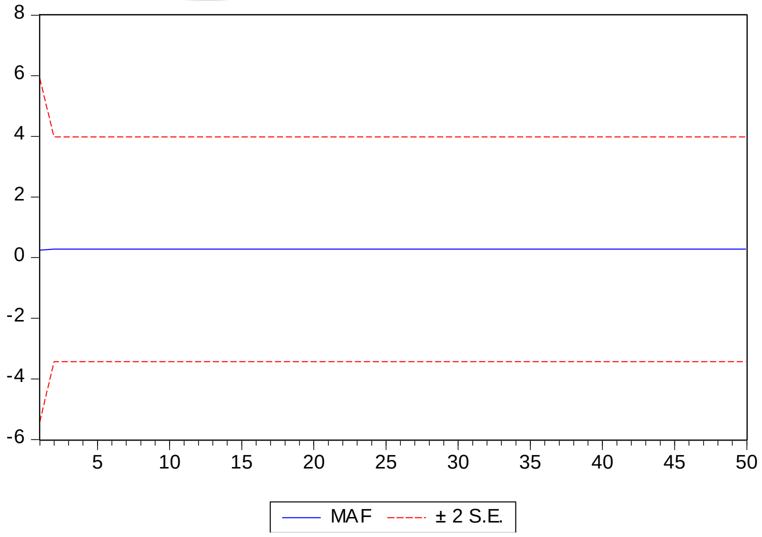
Dependent Variable: Y
Method: Least Squares
Date: 08/16/17 Time: 09:26
Sample: 1 200
Included observations: 200
Convergence achieved after 7 iterations
MA Backcast: 0

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.026671	0.090165	0.295803	0.7677
MA(1)	-0.145768	0.070557	-2.065941	0.0401

R-squared	0.014861	Mean dependent var	0.027471
Adjusted R-squared	0.009886	S.D. dependent var	1.498757
S.E. of regression	1.491331	Akaike info criterion	3.647164
Sum squared resid	440.3653	Schwarz criterion	3.680147
Log likelihood	-362.7164	Hannan-Quinn criter.	3.660512
F-statistic	2.986887	Durbin-Watson stat	1.953649
Prob(F-statistic)	0.085500		

Inverted MA Roots	.15

52. MA forecast N=200 (0.09 high leverage and 1.2 high skewness)



Forecast: MAF
Actual: B
Forecast sample: 1 50
Included observations: 50

Root Mean Squared Error	1.798919
Mean Absolute Error	1.301575
Mean Abs. Percent Error	272.7882
Theil Inequality Coefficient	0.857448
Bias Proportion	0.000000
Variance Proportion	0.995753
Covariance Proportion	0.004246

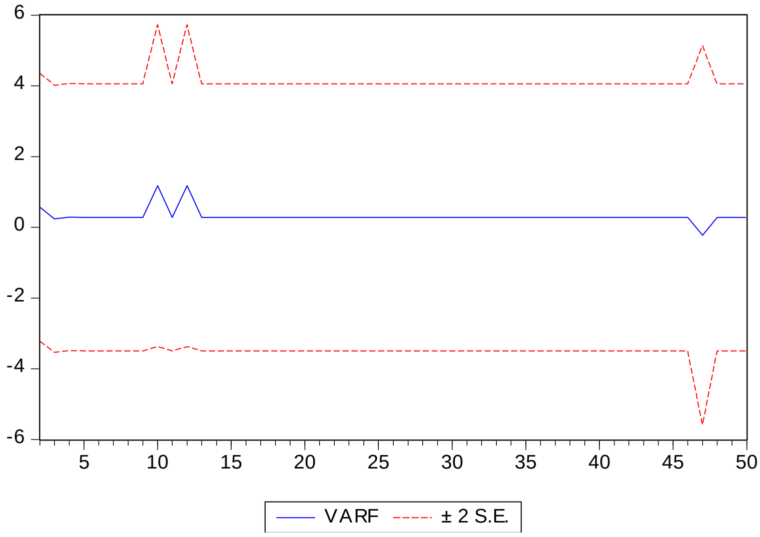
53. VAR estimation N=200 (0.09 high leverage and 1.2 high skewness)

Vector Autoregression Estimates
Date: 08/16/17 Time: 09:40
Sample (adjusted): 2 200
Included observations: 199 after adjustments
Standard errors in ( ) & t-statistics in [ ]

	Y	X30	X35
Y(-1)	-0.102344	-0.001940	0.005068
	(0.07105)	(0.00695)	(0.00572)
	[-1.44047]	[-0.27899]	[0.88634]
X30(-1)	-0.068993	-0.047167	-0.020079
	(0.73120)	(0.07156)	(0.05884)
	[-0.09436]	[-0.65913]	[-0.34123]
X35(-1)	-1.129529	-0.027219	-0.012485
	(0.88841)	(0.08695)	(0.07149)
	[-1.27140]	[-0.31305]	[-0.17463]
C	0.047915	0.033524	0.012731
	(0.10933)	(0.01070)	(0.00880)
	[0.43824]	[3.13304]	[1.44700]
R-squared	0.019188	0.003169	0.004604
Adj. R-squared	0.004099	-0.012166	-0.010710
Sum sq. resids	438.2219	4.197208	2.837929
S.E. equation	1.499097	0.146711	0.120638
F-statistic	1.271653	0.206670	0.300654
Log likelihood	-360.9161	101.5903	140.5292
Akaike AIC	3.667499	-0.980807	-1.372152
Schwarz SC	3.733696	-0.914610	-1.305955
Mean dependent	0.029784	0.031658	0.012060
S.D. dependent	1.502179	0.145827	0.119997

Determinant resid covariance (dof adj.)	0.000702
Determinant resid covariance	0.000661
Log likelihood	-118.5458
Akaike information criterion	1.312018
Schwarz criterion	1.510609

54. VARforecast N=200 (0.09 high leverage and 1.2 high skewness)



Forecast: VARF	
Actual: P	
Forecast sample: 1 50	
Adjusted sample: 2 50	
Included observations: 49	
Root Mean Squared Error	1.788754
Mean Absolute Error	1.295542
Mean Abs. Percent Error	281.9767
Theil Inequality Coefficient	0.815128
Bias Proportion	0.000001
Variance Proportion	0.800990
Covariance Proportion	0.199008

Appendix I

Code for CWN Estimation

The pseudo code for the R software functions for CWN.

```
library(MTS)
library(mnormt)
function (da, q = 1, include.mean = T, fixed = NULL, beta = NULL,
   sebeta = NULL, prelim = F, details = F, thres = 2)
{
   if (!is.matrix(da))
      da = as.matrix(da)
   nT = dim(da)[1]
   k = dim(da)[2]
   if (q < 1)
      q = 1
   kq = k * q
   THini <- function(y, x, q, include.mean) {
      #############
      ############
      ############
     ############
      nT = dim(y)[1]
      k = dim(y)[2]
      ist = 1 + q
      ne = nT - q
      if (include.mean) {
         xmtx = matrix(1, ne, 1)
      }
      else {
         xmtx = NULL
      }
      ymtx = y[ist:nT, ]
      for (j in 1:q) {
```

```
        xmtx = cbind(xmtx, x[(ist - j):(nT - j), ])
    }
    xtx = crossprod(xmtx, xmtx)
    xty = crossprod(xmtx, ymtx)
    xtxinv = solve(xtx)
    beta = xtxinv %*% xty
    resi = ymtx - xmtx %*% beta
    sse = crossprod(resi, resi)/ne
    dd = diag(xtxinv)
    sebeta = NULL
    for (j in 1:k) {
        se = sqrt(dd * sse[j, j])
        sebeta = cbind(sebeta, se)
    }
    THini <- list(estimates = beta, se = sebeta)
  }
  if (length(fixed) < 1) {
    m1 = VARorder(da, p=1, result = FALSE)
    porder = m1$aicor
    if (porder < 1)
        porder = 1
###############
###############
    x = m2$residuals
    m3 = THini(y, x, q, include.mean)
    beta = m3
    sebeta = m3
    nr = dim(beta)[1]
    if (prelim) {
        fixed = matrix(0, nr, k)
        for (j in 1:k) {
            tt = beta[, j]/sebeta[, j]
            idx = c(1:nr)[abs(tt) >= thres]
            fixed[idx, j] = 1
```

```
        }
    }
    if (length(fixed) < 1) {
        fixed = matrix(1, nr, k)
    }
}
else {
    nr = dim(beta)[1]
}
par = NULL
separ = NULL
fix1 = fixed
VMAcnt = 0
ist = 0
if (include.mean) {
    jdx = c(1:k)[fix1[1, ] == 1]
    VMAcnt = length(jdx)
    if (VMAcnt > 0) {
        par = beta[1, jdx]
        separ = sebeta[1, jdx]
    }
    TH = -beta[2:(kq + 1), ]
    seTH = sebeta[2:(kq + 1), ]
    ist = 1
}
else {
    TH = -beta
    seTH = sebeta
}
for (j in 1:k) {
    idx = c(1:(nr - ist))[fix1[(ist + 1):nr, j] == 1]
    if (length(idx) > 0) {
        par = c(par, TH[idx, j])
        separ = c(separ, seTH[idx, j])
```

```
    }
}
ParMA <- par
LLKvma <- function(par, zt = zt, q = q, fixed = fix1, include.mean = include.mean) {
    k = ncol(zt)
    nT = nrow(zt)
    mu = rep(0, k)
    icnt = 0
    VMAcnt <- 0
    fix <- fixed
    iist = 0
    if (include.mean) {
        iist = 1
        jdx = c(1:k)[fix[1, ] == 1]
        icnt = length(jdx)
        VMAcnt <- icnt
        if (icnt > 0)
            mu[jdx] = par[1:icnt]
    }
    for (j in 1:k) {
        zt[, j] = zt[, j] - mu[j]
    }
    kq = k * q
    Theta = matrix(0, kq, k)
    for (j in 1:k) {
        idx = c(1:kq)[fix[(iist + 1):(iist + kq), j] == 1]
        jcnt = length(idx)
        if (jcnt > 0) {
            Theta[idx, j] = par[(icnt + 1):(icnt + jcnt)]
            icnt = icnt + jcnt
        }
    }
    TH = t(Theta)
    if (q > 1) {
```

```
    tmp = cbind(diag(rep(1, (q - 1) * k)), matrix(0,
        (q - 1) * k, k))
    TH = rbind(TH, tmp)
}
mm = eigen(TH)
V1 = mm
P1 = mm
v1 = Mod(V1)
ich = 0
for (i in 1:kq) {
    if (v1[i] > 1)
        V1[i] = 1/V1[i]
    ich = 1
}
if (ich > 0) {
    P1i = solve(P1)
    GG = diag(V1)
    TH = Re(P1 %*% GG %*% P1i)
    Theta = t(TH[1:k, ])
    ist = 0
    if (VMAcnt > 0)
        ist = 1
    for (j in 1:k) {
        idx = c(1:kq)[fix[(ist + 1):(ist + kq), j] ==
          1]
        jcnt = length(idx)
        if (jcnt > 0) {
          par[(icnt + 1):(icnt + jcnt)] = TH[j, idx]
          icnt = icnt + jcnt
        }
    }
}
at = mFilter(zt, t(Theta))
sig = t(at) %*% at/nT
```

```
    ll = dmvnorm(at, rep(0, k), sig)
    LLKvma = -sum(log(ll))
    LLKvma
  }
  cat("Number of parameters: ", length(par), "\n")
  cat("initial estimates: ", round(par, 4), "\n")
  lowerBounds = par
  upperBounds = par
  npar = length(par)
  mult = 2
  if ((npar > 10) || (q > 2))
    mult = 1.2
  for (j in 1:npar) {
    lowerBounds[j] = par[j] - mult * separ[j]
    upperBounds[j] = par[j] + mult * separ[j]
  }
  cat("Par. Lower-bounds: ", round(lowerBounds, 4), "\n")
cat("Par. Upper-bounds: ", round(upperBounds, 4), "\n")
  if (details) {
    fit = nlminb(start = ParMA, objective = LLKvma, zt = da,
      fixed = fixed, include.mean = include.mean, q = q,
      lower = lowerBounds, upper = upperBounds, control = list(trace = 3))
  }
  else {
    fit = nlminb(start = ParMA, objective = LLKvma, zt = da,
      fixed = fixed, include.mean = include.mean, q = q,
      lower = lowerBounds, upper = upperBounds)
  }
  epsilon = 1e-04 * fit$par
  npar = length(par)
  Hessian = matrix(0, ncol = npar, nrow = npar)
  for (i in 1:npar) {
    for (j in 1:npar) {
      x1 = x2 = x3 = x4 = fit
```

```
        x1[i] = x1[i] + epsilon[i]
        x1[j] = x1[j] + epsilon[j]
        x2[i] = x2[i] + epsilon[i]
        x2[j] = x2[j] - epsilon[j]
        x3[i] = x3[i] - epsilon[i]
        x3[j] = x3[j] + epsilon[j]
        x4[i] = x4[i] - epsilon[i]
        x4[j] = x4[j] - epsilon[j]
        Hessian[i, j] = (LLKvma(x1, zt = da, q = q, fixed = fixed,
          include.mean = include.mean) - LLKvma(x2, zt = da,
          q = q, fixed = fixed, include.mean = include.mean) -
          LLKvma(x3, zt = da, q = q, fixed = fixed, include.mean = include.mean) +
          LLKvma(x4, zt = da, q = q, fixed = fixed, include.mean = include.mean))/(4 *
          epsilon[i] * epsilon[j])
    }
}
est = fit$par
cat("Final   Estimates: ", est, "\n")
se.coef = sqrt(diag(solve(Hessian)))
tval = fit$par/se.coef
matcoef = cbind(fit$par, se.coef, tval, 2 * (1 - pnorm(abs(tval))))
dimnames(matcoef) = list(names(tval), c(" Estimate", " Std. Error",
    " t value", "Pr(>|t|)"))
cat("\nCoefficient(s):\n")
printCoefmat(matcoef, digits = 4, signif.stars = TRUE)
cat("---", "\n")
cat("Estimates in matrix form:", "\n")
icnt = 0
ist = 0
cnt = NULL
if (include.mean) {
    ist = 1
    cnt = rep(0, k)
    secnt = rep(1, k)
```

```
    jdx = c(1:k)[fix1[1, ] == 1]
    icnt = length(jdx)
    if (icnt > 0) {
        cnt[jdx] = est[1:icnt]
        secnt[jdx] = se.coef[1:icnt]
        cat("Constant term: ", "\n")
        cat("Estimates: ", cnt, "\n")
    }
}
cat("MA coefficient matrix", "\n")
TH = matrix(0, kq, k)
seTH = matrix(1, kq, k)
for (j in 1:k) {
    idx = c(1:kq)[fix1[(ist + 1):nr, j] == 1]
    jcnt = length(idx)
    if (jcnt > 0) {
        TH[idx, j] = est[(icnt + 1):(icnt + jcnt)]
        seTH[idx, j] = se.coef[(icnt + 1):(icnt + jcnt)]
        icnt = icnt + jcnt
    }
}
icnt = 0
for (i in 1:q) {
    cat("MA(", i, ")-matrix", "\n")
    theta = t(TH[(icnt + 1):(icnt + k), ])
    print(theta, digits = 3)
    icnt = icnt + k
}
zt = da
if (include.mean) {
    for (i in 1:k) {
        zt[, i] = zt[, i] - cnt[i]
    }
}
```

```
   at = mFilter(zt, t(TH))
   sig = t(at) %*% at/nT
   cat(" ", "\n")
   cat("Residuals cov-matrix:", "\n")
   print(sig)
   dd = det(sig)
   d1 = log(dd)
   aic = d1 + 2 * npar/nT
   bic = d1 + log(nT) * npar/nT
   cat("----", "\n")
   cat("aic= ", aic, "\n")
   cat("bic= ", bic, "\n")
   Theta = t(TH)
   if (include.mean) {
      TH = rbinds(cnt, TH)
      seTH = rbind(secnt, seTH)
   }
VMA<list(data=da,MAorder=q,cnst=include.mean,coef=TH,se=seTH,residuals=at,Sigma=sig,
aic=aic,bic=bic)
```