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程序代写代做CS编程辅导

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1. (Miscellaneous questions)

(a) The condition of a vector of returns is useful for designing “mean-variance efficient” portfolios. A mean-variance efficient portfolio on a given set of assets is one that has the minimum variance for a given desired mean return. Consider one-day ahead problem with n assets. Let $r = [r_1, \dots, r_n]'$ be the vector of the 1-day returns for the assets.

The mean of r , $\mu = E(r) = [\mu_1, \dots, \mu_n]'$, is also an n dimensional vector. The variance of r ,

$$V = \text{Var}(r) = \begin{bmatrix} V_{11} & \dots & V_{1n} \\ \vdots & \ddots & \vdots \\ V_{n1} & \dots & V_{nn} \end{bmatrix} = \begin{bmatrix} \text{Var}(r_1) & \dots & \text{Cov}(r_1, r_n) \\ \vdots & \ddots & \vdots \\ \text{Cov}(r_n, r_1) & \dots & \text{Var}(r_n) \end{bmatrix},$$

is an $n \times n$ dimensional matrix. Because the covariances are symmetric $\text{Cov}(r_i, r_j) =$

$\text{Cov}(r_j, r_i)$, the matrix V is symmetric with $V_{ij} = V_{ji}$ for all i and j . Suppose that you invest a portion of your wealth, w_i , in asset i , for $i = 1, \dots, n$, where $\sum_{i=1}^n w_i = 1$. Then your portfolio

is determined by the weight vector $w = [w_1, \dots, w_n]'$ and your portfolio return is given by

$r_p = \sum_{i=1}^n w_i r_i = w' r$ with the mean $\mu_p = E(r_p) = \sum_{i=1}^n w_i \mu_i = w' \mu$ and variance $\sigma_p^2 =$

$\text{Var}(r_p) = w' V w$. To obtain the mean-variance efficient portfolio, you choose w to minimise

the variance $w' V w$ for a given mean return μ_p . Because the weights in w can be any set of

numbers with $\sum_{i=1}^n w_i = 1$ and the portfolio return variance σ_p^2 must be non-negative, a

variance matrix V must be such that $w' V w \geq 0$ for any w with $\sum_{i=1}^n w_i = 1$ (ie, V must be

semi-positive definite). Hence a variance matrix V is required to be symmetric and semi-positive definite.

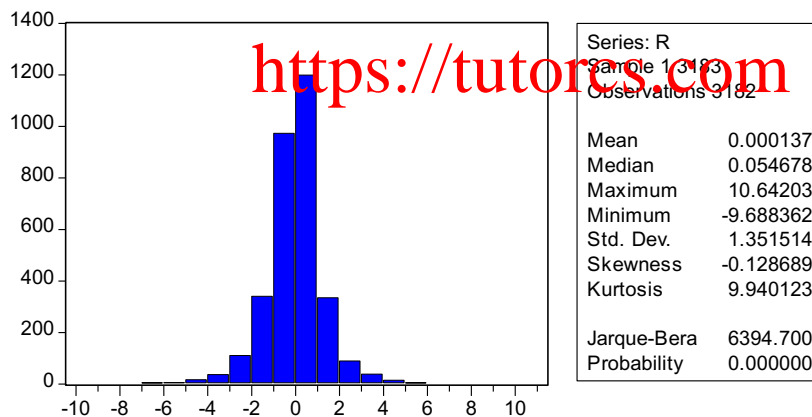
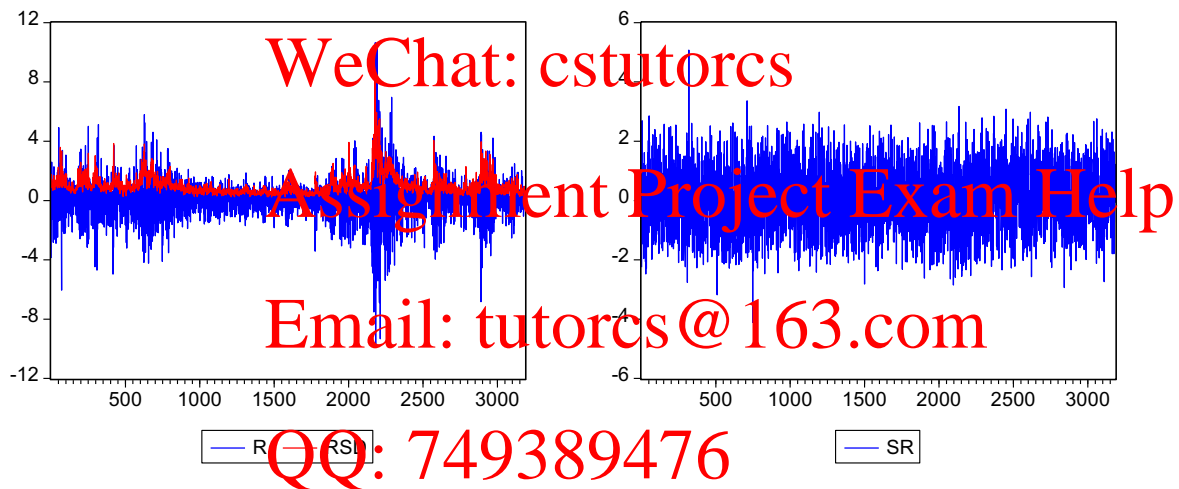
(b) The daily realised variance (RV) of an asset return is constructed from the intraday returns, eg, intraday 5-minute returns. Originally, the RV is computed as the sum of the squared intraday returns. However, there are alternative (and better) ways to compute the RV. The daily RV is an estimate of the integrated variance, which can be regarded as the spot or instantaneous variance of the return.

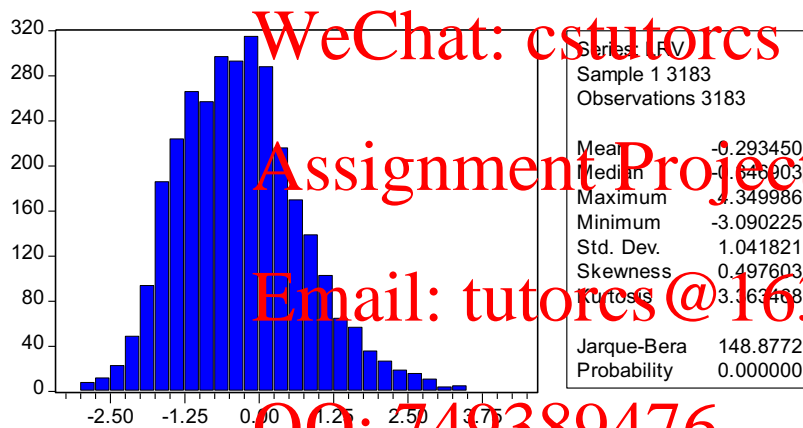
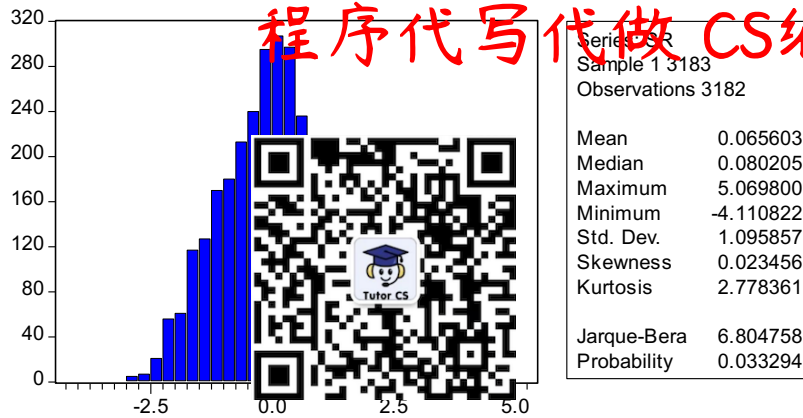
2. (Realised volatility, data source: <http://realized.oxford-man.ox.ac.uk/data>)

(a) The time series plots show that the variations in R are accurately mirrored in the levels of RSD. The difference between the plots of R and SR provides a sharp contrast: the

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clustering in R is mostly attributable to BSD. The histogram and descriptive statistics of R show the usual return characteristics: close-to-zero mean, large standard deviation, negative skewness, large kurtosis, and decisively non-normal. However, the histogram and descriptive statistics of SR are r of a standard normal random variable, although the null hypothesis of n ed at the 5% level (p-value 0.033). Notice that SR is standardised by using the unconditional realised variance, which is NOT the conditional variance. The RV indicates that it is positively skewed with a kurtosis greater than 3, roughly bell shaped but non-normal.





(b) There are statistically significant (with small magnitudes) autocorrelations in R according to correlograms below. The autocorrelations in LRV are large and long-lasting. In particular, the autocorrelations in LRV do not appear to converge to zero quickly as the lag increases. That is, the decay of the autocorrelations does not appear to be exponential.

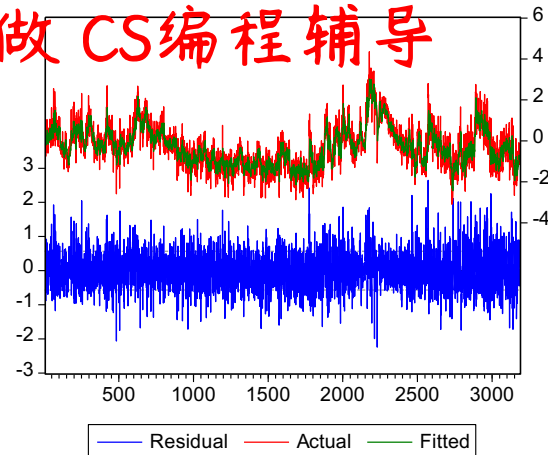


(c) The augmented Dickey-Fuller test on LRV rejects the null hypothesis of a unit-root. Hence, the evidence suggests that LRV is still stationary despite its large and long-lasting autocorrelations. To fit an ARMA model to LRV, the partial autocorrelations suggest that an AR(11) would be a candidate (2 standard error band $2/\sqrt{T} \approx 0.035$, any AC or PAC within the bands are statistically zero). Here, maybe incorrectly, we assume the autocorrelations exponentially decay to zero. The estimation results show that most of the AR coefficients are statistically significant (except lags 6,7,9 and 10). More than 70% of the variations in LRV are explained by the AR(11) model. The actual-fitted-residual plot demonstrates that the model fits the data well. The correlogram of the residuals shows little autocorrelation. Hence the AR(11) model has done a good job in capturing the autocorrelations in LRV, although the true data-generating-process could be a long-memory ARFIMA model. From the residual histogram below, the residual distribution is not normal with positive skewness and heavy tails, although it is roughly bell-shaped. The main point of this part is that the long-lasting autocorrelations of LRV can be approximately captured by an AR(p) with a moderately large p (here we have $p = 11$).

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Augmented Dickey-Fuller test	
Null Hypothesis: LRV has a unit root	
Exogenous: Constant	
Lag Length: 7 (Automatic base)	
Augmented Dickey-Fuller test statistic	
Test critical values:	1% level -2.567193
	5% level -1.959560
	10% level -1.604746

*MacKinnon (1996) one-sided p-values.



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Dependent Variable: LRV
Method: Least Squares

Sample (adjusted): 12 3183

Included observations: 3172 after adjustments

Convergence achieved after 3 iterations

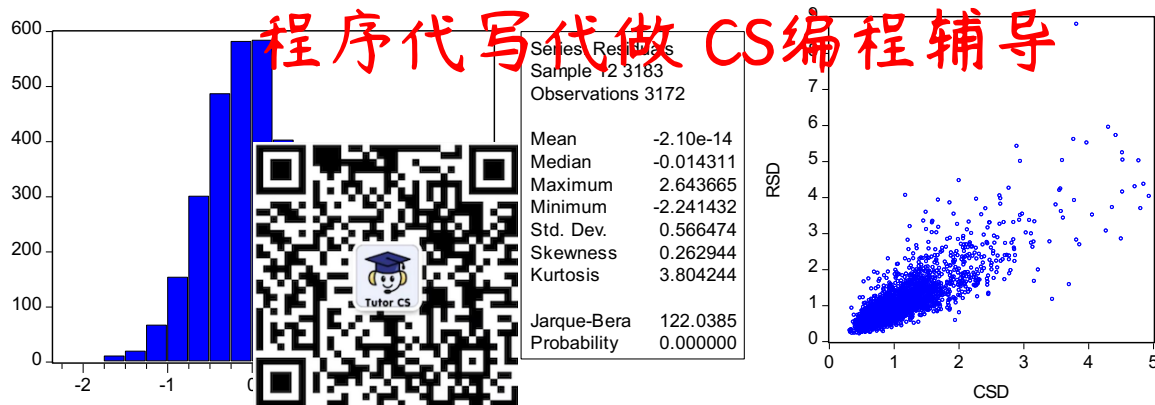
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	-0.312751	0.171904	-1.819333	0.0690
AR(1)	0.352555	0.017767	19.84250	0.0000
AR(2)	0.205171	0.018835	10.8937	0.0000
AR(3)	0.082500	0.019186	4.300025	0.0000
AR(4)	0.092932	0.019229	4.833018	0.0000
AR(5)	0.071244	0.019304	3.690581	0.0002
AR(6)	0.003165	0.019346	0.163608	0.8700
AR(7)	0.005566	0.019303	0.288337	0.7731
AR(8)	0.040333	0.019233	2.097080	0.0361
AR(9)	0.024005	0.019185	1.251233	0.2109
AR(10)	0.014099	0.018835	0.748551	0.4542
AR(11)	0.049803	0.017761	2.804105	0.0051
R-squared	0.704864	Mean dependent var	-0.295525	
Adjusted R-squared	0.703837	S.D. dependent var	1.042723	
S.E. of regression	0.567459	Akaike info criterion	1.708479	
Sum squared resid	1017.551	Schwarz criterion	1.731413	
Log likelihood	-2697.648	F-statistic	686.0859	
Durbin-Watson stat	2.002453	Prob(F-statistic)	0.000000	
Inverted AR Roots	.98	.66-.39i	.66+.39i	.29+.67i
	.29-.67i	-.06+.73i	-.06-.73i	-.50+.56i
	-.50-.56i	-.71+.20i	-.71-.20i	

Sample: 12 3183

Included observations: 3172

Q-statistic probabilities adjusted for 11 ARMA term(s)

Autocorrelation	Partial Correlation	AC	PAC	Q-Stat	Prob
1	-0.002	-0.002	0.0083		
2	-0.001	-0.001	0.0108		
3	-0.002	-0.002	0.0284		
4	0.003	-0.003	0.0521		
5	-0.004	-0.004	0.1025		
6	-0.003	-0.003	0.1271		
7	-0.007	-0.007	0.2665		
8	-0.008	-0.008	0.4907		
9	-0.008	-0.008	0.7091		
10	-0.015	-0.015	1.4392		
11	-0.026	-0.026	3.6017		
12	0.007	0.006	3.7442	0.053	
13	-0.012	-0.012	4.1815	0.124	
14	0.002	0.001	4.1898	0.242	
15	0.002	0.001	4.1998	0.380	
16	0.002	0.001	4.2101	0.520	
17	-0.028	-0.028	6.6871	0.351	
18	-0.015	-0.016	7.3904	0.389	
19	0.022	0.021	8.9368	0.348	
20	-0.001	-0.002	8.9405	0.443	
21	-0.009	-0.010	9.2105	0.512	
22	0.028	0.028	11.804	0.379	
23	0.007	0.007	11.977	0.448	
24	-0.017	-0.018	12.906	0.455	
25	-0.041	-0.041	18.199	0.198	
26	-0.011	-0.012	18.603	0.232	
27	0.002	0.001	18.614	0.289	
28	-0.006	-0.008	18.741	0.344	
29	-0.009	-0.009	19.011	0.391	
30	0.027	0.028	21.314	0.320	
31	0.005	0.004	21.384	0.375	
32	-0.037	-0.038	25.886	0.211	
33	0.031	0.031	28.908	0.147	
34	0.014	0.012	29.566	0.162	
35	0.003	0.000	29.603	0.198	
36	0.015	0.014	30.335	0.212	



(d) The scatter plot above shows the connection and difference between the conditional volatility estimates (CSD) and the spot or instantaneous volatility estimates (RSD). The CSD can be regarded as a point forecast of RSD.

(e) The estimation results of EGARCH(2,1) below shows that the model has adequately represented the clustering in the return R_t , as the ARCH test does not reject the null hypothesis of no ARCH effect in the standardised residuals. The time series and scatter plots show the similarities and differences between the conditional standard deviation from EGARCH and the conditional standard deviation based on LRV. While EGSD and CSD differ markedly, they have extremely strong cross-correlations (see the cross-correlogram below). For example, the static correlation is almost perfect (0.9285).

Estadistic	0.51144	Probability	0.853196
Obs*R-squared	6.300539	Probability	0.852578

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.943109	0.064534	14.61414	0.0000
STD_RESID*2(-1)	0.005062	0.035266	0.143540	0.8859
STD_RESID*2(-2)	0.008608	0.017323	0.496885	0.6193
STD_RESID*2(-3)	-0.023500	0.013776	-1.705877	0.0881
STD_RESID*2(-4)	-0.003841	0.014189	-0.270678	0.7867
STD_RESID*2(-5)	0.012061	0.015728	0.766866	0.4432
STD_RESID*2(-6)	-0.006952	0.013672	-0.508474	0.6112
STD_RESID*2(-7)	0.023840	0.022081	1.079664	0.2804
STD_RESID*2(-8)	0.002116	0.014556	0.145408	0.8844
STD_RESID*2(-9)	0.009801	0.017094	0.573384	0.5664
STD_RESID*2(-10)	0.018366	0.017243	1.065147	0.2869
STD_RESID*2(-11)	0.012033	0.014944	0.805208	0.4208

R-squared	0.001988	Mean dependent var	1.000895
Adjusted R-squared	0.007489	S.D. dependent var	1.729191
S.E. of regression	1.753927	Akaike criterion	0.0348
Sum squared resid	10190.20	Schwarz criterion	4.036089
Log likelihood	-6348.832	F-statistic	0.571744
Durbin-Watson stat	2.000136	Prob(F-statistic)	0.853196

A scatter plot showing the relationship between CSD (x-axis) and CSD (y-axis) for the 1000th iteration. The data points are blue circles, forming a dense, elongated cluster along the diagonal line y=x, indicating a strong positive correlation. The axes range from 0 to 5.

Jarque-Bera	283.9731
Probability	0.000000

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(f) The estimation results below confirms that the dependence structure of R is well captured by the extended AR(1)-EGARCH(2,1). No statistically-significant autocorrelations are observed in either residuals or their squares (see ARCH test as well as correlograms below). LRV(-1) is large and statistically significant, implying that LRV_{t-1} contains valuable information that is not available in either v_{t-1} , v_{t-2} or $\ln(\sigma_{t-1}^2)$. The model is materially improved with the likelihood ratio being $LR = 2[(-4548.36) - (-4642.39)] = 188.06$ (compared against $\chi^2_{(1)}$ 5% critical value 3.84). The AIC and SIC criteria also favour the inclusion of LRV(-1) in the variance equation. The point estimate of β_1 is 0.7719, much smaller than the estimate 0.9762 in part (e). However, the persistence in the conditional variance of EGARCH that includes LRV(-1) should be measured differently. It should depend on both β and the coefficient on LRV(-1), b , probably in a complicated way.



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Dependent Variable: R
Method: ML - ARCH (Marquardt) - Normal distribution

Sample (adjusted): 3 3183

Included observations: 3181 after adjustments

Convergence achieved after 16 iterations

Bollerslev-Wooldridge robust standard errors & covariance

Variance backcast: ON

LOG(GARCH) = C(3) + C(4)*ABS(RESID(-1)/@SQRT(GARCH(-1))) +
C(5)*ABS(RESID(-2)/@SQRT(GARCH(-2))) + C(6)*RESID(-1)
/@SQRT(GARCH(-1)) + C(7)*LOG(GARCH(-1)) + C(8)*LRV(-1)

	Coefficient	Std. Error	t-Statistic	Prob.
C	0.006952	0.014012	0.496143	0.6198
AR(1)	-0.046619	0.015392	-3.028768	0.0025
Variance Equation				
C(3)	0.169376	0.041642	4.067440	0.0000
C(4)	-0.317796	0.055023	-5.775660	0.0000
C(5)	0.188086	0.046006	4.088320	0.0000
C(6)	-0.177266	0.018350	-9.660251	0.0000
C(7)	0.771866	0.031834	24.24693	0.0000
C(8)	0.221003	0.031880	6.932430	0.0000
R-squared	0.005363	Mean dependent var	0.001357	
Adjusted R-squared	0.003169	S.D. dependent var	1.349975	
S.E. of regression	1.347835	Akaike info criterion	2.864734	
Sum squared resid	5764.258	Schwarz criterion	2.879987	
Log likelihood	-4548.360	F-statistic	2.444080	
Durbin-Watson stat	2.074423	Prob(F-statistic)	0.016912	
Inverted AR Roots	-.05			

ARCH Test:

F-statistic	0.418546	Probability	0.948689
Obs*R-squared	4.614767	Probability	0.948380

Test Equation:

Dependent Variable: STD_RESID^2

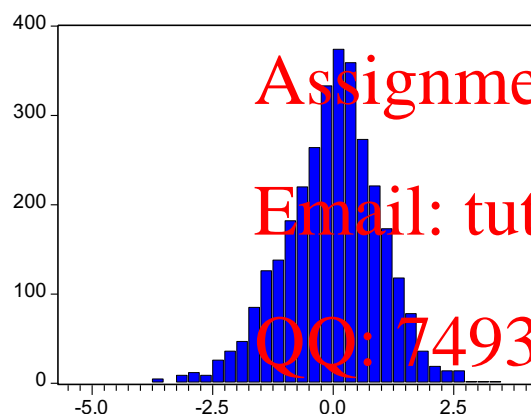
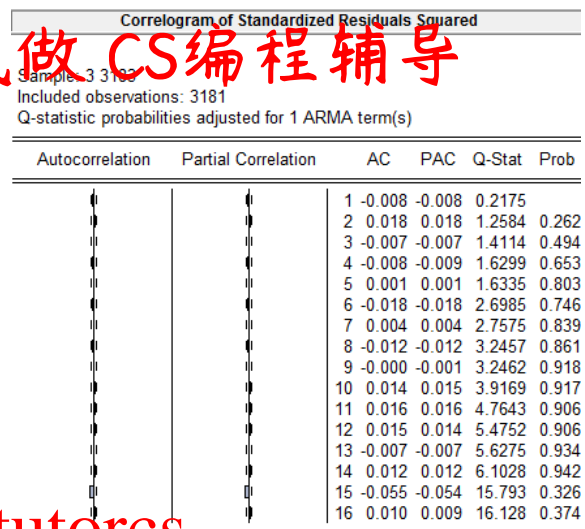
Method: Least Squares

Sample (adjusted): 14 3183

Included observations: 3170 after adjustments

White Heteroskedasticity-Consistent Standard Errors & Covariance

Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	0.999512	0.069689	14.34255	0.0000
STD_RESID^2(-1)	-0.008288	0.020747	-0.399457	0.6896
STD_RESID^2(-2)	0.018144	0.018819	0.964146	0.3350
STD_RESID^2(-3)	-0.006367	0.020036	-0.317795	0.7507
STD_RESID^2(-4)	-0.008246	0.014231	-0.579442	0.5623
STD_RESID^2(-5)	0.001070	0.017501	0.061135	0.9513
STD_RESID^2(-6)	-0.017404	0.014033	-1.240273	0.2150
STD_RESID^2(-7)	0.004411	0.017841	0.247217	0.8048
STD_RESID^2(-8)	-0.011805	0.013867	-0.851298	0.3947
STD_RESID^2(-9)	-0.001033	0.016356	-0.063170	0.9496
STD_RESID^2(-10)	0.015271	0.020076	0.760638	0.4469
STD_RESID^2(-11)	0.015435	0.016396	0.941373	0.3466
R-squared	0.001456	Mean dependent var	1.000700	
Adjusted R-squared	-0.002022	S.D. dependent var	1.655155	
S.E. of regression	1.656828	Akaike info criterion	3.851465	
Sum squared resid	8668.960	Schwarz criterion	3.874411	
Log likelihood	-6092.572	F-statistic	0.418546	
Durbin-Watson stat	2.000321	Prob(F-statistic)	0.948689	



Series: Standardized Residuals
Sample: 3 3183
Observations: 3181

Mean	-0.004635
Median	0.071906
Maximum	3.779356
Minimum	-5.438911
Std. Dev.	0.999997
Skewness	-0.327574
Kurtosis	3.727077
Jarque-Bera	126.9562
Probability	0.000000

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