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AUTOCORRELATION: WHAT HAPPENS IF THE ERROR OR DISTURBANCE TERMS ARE CORRELATED IN TIME-SERIES DATA

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ABSTRACT

This research explores the econometric investigation of emblematic and well-acknowledged subjects over the years, such as serial correlation, also known as autocorrelation, where error terms in a time series data transfer from one-time period to another. This inquiry explores a few major and central foundations of autocorrelation terminologies. Furthermore, this study will enlighten the cause and remedies for the classical assumption named autocorrelation. This problematic term in time series data analysis arises because exogenous seems dissimilar dimensionally with Predict, but errors are not independently acting. It violates the assumption of linear regression where model indicators or one of the explanatory variables is the lagged value of the dependent with the same quantified amount of errors from a one-time period shifted in pattern to the subsequent. Correspondingly omitted variables or essential exogenous are absent or deleted cause their effect on the dependent variable becomes part of the error term. Hence, this paper has employed suitable heteroscedasticity-consistent (HC) and heteroscedasticity, cross correlogram, and autocorrelation consistent (HAC) estimators. In this inquiry, Eviews for statistical computation is utilized and show how variables' suggested functioning and behaviour. This study employed five economic indicators to show the autocorrelation cause and its remedial measure (2003 to 2020).

Keywords: Autocorrelation, Error correction term, Time-series data, serial correlation

INTRODUCTION

Autocorrelation is where the error terms transference in a time series data from one-time period to subsequent (Maddala & Lahiri, 1992). In addition, the error for a one-time period (a) is correlated with the error for a subsequent period (b). For example, underestimating one quarter's profits can result in an underestimate of profits for the subsequent quarter. In addition, the error for a one-time period a is correlated with the error for a subsequent period b (Gujarati, Porter & Gunasekar, 2012). An underestimated value for one quarter's profits can result in an underestimated profit for succeeding.

There is an assumption in the linear model that the random error disturbances are identical and independently distributed. This can cause numerous complications, including Ineffective OLS Estimations. An effective estimator provides the utmost evidence; inefficient estimators can perform well but necessitate much larger sample sizes. Cochrane & Orcutt (1949) Overstated goodness of fit (for a time series with positive serial correlation and an independent variable that grows over time (Gujarati, Porter & Gunasekar, 2012). T-stat is too large to be real, Deceitful positives for significant regression coefficients. McLeod (1978), the most common form of autocorrelation is a first-order serial correlation, which can either be positive or negative. Cochrane & Orcutt, (1949) Positive autocorrelation happens when one period's error carries to the next period. For example, two variables escalate together for a positive correlation or decline. For example, the number of gallons of gas pumped is positively correlated to the amount spent on gas, so when you spend more on the gas, the number of gallons of gas pumped will increase as you realize both are increasing (Wei, 2006).

This research is focused on inspecting the significance of econometric problem autocorrelation and the assumption of linear regression where disturbance ε of the indicators are not independently come about or befalls in time series. Furthermore, this empirical testing for autocorrelation will enlighten the detection, cause, and remedial measures with statistical and econometric software E-views. Questions are framed in understanding objectives by how autocorrelation is present in the times series data and the remedial measure.

- What are the hypothetical and functional extents of autocorrelation in time series?
- How does one recognize or detect that there is autocorrelation in a few specified circumstances?
- By what method does one remedy the problematic area in time series?
- The central objectives are:
- To inspect how autocorrelation affects the results with and without this problem
- To examine whether this has to be the situation where autocorrelation is pure autocorrelation that seems to be or the consequences of a mis-specified model in the research or collaboration that has led us to errors heteroscedasticity.
- To examine how this problem will cause and what remedial measures are effective in these circumstances

LITERATURE REVIEW:

Guggenberger, Kleibergen & Mavroeidis (2021) present an innovative test for a two-sided hypothesis comprising a division of the basic parameter vector in the linear variables (IVs) model, with an asymptotic size equivalent to a minimal size for a parameter that allows for strength or weakness of the IVs. Ali & Midi (2020) the scholars revealed research about COPW, which explored COPW performs better than some existing methods in autocorrelated errors, vertical outliers, and bad leverage points.

Uyanto (2020) states that the foremost cause of autocorrelation is sometimes an absence of indicators from the model, and we cannot comprehend it. When an essential exogenous factor is omitted in the model, its effect on the dependent variable becomes part of the error term. Therefore, if the omitted indicator has a positive or negative correlation with the response, it probably causes error terms that are positively or negatively correlated.

Sani, Midi & Arasan, (2019) and Felsenstein & Churchill, (1996) Second-order serial correlation we say is when an error affects data two time periods later. Seasonal data usually possesses this quality in second-order; however, it is rare. Maleki, Amiri & Taheriyoun's (2017) inheritance of effect, at minimum in quantity, is an important birthplace of autocorrelation. The previous month's spending influences the monthly statistics on domestic (households) expenses.

Gujarati, Porter & Gunasekar, 2012) the issue existent in cross-section statistics and time series sequence data. Removal of some variables Causes autocorrelation is the expected effect. In regression modeling, taking in all the variables related to research is not possible. (Maddala & Lahiri, 1992) Plenty of variables in the former studies will hopefully play a vital and significant role in forecasting the dependent prediction. Among them, the scholar has to decide which variables must be added to the model as all tend to find natural difficulty to adjust with each other.

There can be numerous whys and wherefores for this, and some variables may be in qualitative nature (dummy) dichotomous or polychotomous sometimes, direct annotations or explanations may not be available on the variable, etc. (Gao, Cheng, et al. 201 Gao, Cheng, Meng & Liu, 2019). The combined effect of such removed indicators gives intensification to autocorrelation. Various scholars and statisticians have tried to explore the issue of pure autocorrelation, such as Gujarati 2008, C Dougherty (2011) and M. Verbeek. These scholars have touched on the concept mathematically only, the hetro and auto in parallel concerning the time series data, but never showed the practical impact on the results in time series. This paper emphasized the differentiation between pure autocorrelation and heteroscedasticity in practical empirically demonstrated with before and after remedial measures taken to remove the problem of the first level of errors terms transformation.

Moreover, this research paper has demonstrated graphical analysis with the help of E-views (statistical software) to show this issue and remove errors transformation of multiple periods without deleting any outlier in the datasheet. The major issue enlightened or addressed in this research paper was exploring the autocorrelation in time series and how it is being removed from the data to eliminate the problem that has affected the results significantly. Therefore, showing before-after effect results with and without autocorrelation. This econometric problem was previously introduced by scholars but has never been tried practically or in pictorial form through software.

RESEARCH METHODOLOGY:

This section covers the methodology of this investigation which will assist in the demonstration of outcomes from the time series in a logical fashion. Kleibergen (2021) states that Markov first level autoregressive assumes that the error that occurred in the current time is linearly allied or interrelated to the error in the prior period. In this empirical investigation, we have shown this problem with several techniques. The HAC test and cross correlogram show a pattern in the fallouts and effects before and after applying the testing for autocorrelation. Any values above zero should be looked at with suspicion. Before and after-effects will be demonstrated. Firstly, it is enlightening how one should duct it, and secondly, what are the remedial techniques to show unbiased linear equation. Thirdly, Challenge is to analyze whether this has to be the situation where autocorrelation is pure autocorrelation that seems to be and not the consequences of the mis-specified model in the research or collaboration that has led us to errors of heteroscedasticity. Meitz et al., (2021) If we see ourselves in the situation where pure autocorrelation appears, one can utilize suitable conversion of the basic model so that we only treat the problem of exact autocorrelation in the transmuted model. Fourthly**,** in gigantic samples (Turner, Forbes, Karahalios, Taljaard & McKenzie, 2021), we might feasibly utilize the Newey West testing tools to acquire errors used to make rectifications for autocorrelation. The corrected standard errors are known as HAC or perused Newey errors. When we compact the techniques of newly, it is assumed and testified dynamic that this test only proves its validity and accuracy on a larger sample; in contrast, a small sample will not be suitable (Ching & Phoon, 2019). The time series data of 145 observations are utilized from the Pakistan stock exchange and economic survey of Pakistan of economic indicators such as stock index variation, revenue, expenditures, inflation rate, interest, and exports.

The first difference function utilization meant Gujarati, Porter & Gunasekar (2012) to be that if the statistician by dropping the first Observation value in the data, the chain of errors transferring from one time to subsequent will be discontinued and will not fall in the next period in the manner as it was behaving before. If the coefficient of autocorrelation is exaggerated from 0.8, or the Durbin W is nearly zero (Kim, 2021) as a rule of thumb. We used the first difference form whenever d < R2, where we found d=0.1229 and r^2 =0.958. This is the most eminent test identifying serial correlation developed by J. Durbin and G S Watson (1951).

$$D= \frac{\sum_{t=2}^{n}(\widehat{u_t}-\widehat{u_{t-1}})^2}{\sum_{t=2}^{n}\widehat{u_t}^2}$$

The hypothesis of the investigation:

H0: There is no pure autocorrelation in the model H1: There is pure autocorrelation in the model

RESULTS AND DISCUSSION:

In this inquiry, the direct estimation is conducted to establish the error term's autocorrelation. Therefore, remedial measures are applied in certain circumstances to detect pure autocorrelation and show its cause. Various tests demonstrate the effectiveness of tools and techniques to remove the problem area in this inquiry.

Table 4.1 Detection for pure autocorrelation

Original model				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.1410	8.4909	2.516430	0.0130
EXM	0.6360	0.0126	33.82627	0.0000
SI	15433.	2114.6	7.328201	0.0000
INF	4.9108	2.1508	2.279173	0.0242
INTR	-9.0608	7.4308	-1.218582	0.2251
EXPO	-9.7400	5.0847	-1.915869	0.0574
R-squared	0.985	F-statistic		13.41880
Adjusted R-squared	0.9848	Durbin Watson		0.5551

The outcome from (table 4.1) revealed five regressors in the model with 145 observations showing a significant probability value (0000) of all independent indicators except one, which explores that the actual result is in favor of the research. The value of the Durbin Watson stat (0.5551) led to the provision of autocorrelation as this value must not be close to zero. Durbin-Watson is (0.5551) less than 1.68 and 1.96, showing autocorrelation in indicator predict Random Effect Model (Basheer et al., 2019; Hidthiir, et al., 2019; Basheer et al., 2018: Basheer et al., 2021). Furthermore, R/Sq and Adj R/Sq are 0.985 and 0.984, respectively, which highly enlightens more than a standard parameter and over variance in the model. It also concluded the first objective of the study, the results with the element of autocorrelation in the time series data.

Table 4.2 Breusch-Godfrey Serial Correlation LM Test

F-stat	182.8104	Prob. F(1,138)	0.00000
Obs R-sqD	82.62672	ProbChi-Square(1)	0.00000

The result from the above breusch G (table 4.2) of the serial LM test detected and exposed the factor of pure correlation through the p-value (0.000) of Chi-square. Secondly, by Establishing the problem in the model, it led us to the rule calculated by the various statistics such as (Gujarati, Porter & Gunasekar, 2012; Basheer et al, 2019b; Basheer et al., 2020b)) value must not be less than 0.05 if this value is lesser than (0.05) we say according to the empirical assumption and properties this has to be the case for pure serial correlation.

Table 4.3 Heteroscedasticity Breusch Pagan Godfrey

F-statistic	6.697759	Prob. F(5,139)	0.0000
ObsR-sqd	28.15183	Prob. Chi-Square	0.6700
Scaled explained SS	43.69041	Prob. Chi-Square	0.0000

Table 4.4 Dependent Variable: REM

HAC standard errors & covariance (Bartlett kernel, Newey-West fixed

Original model				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	2.1410	1.2010	1.784818	0.0765
EXM	0.6060	0.0408	14.71460	0.0000
SI	15493.	6823.2	2.272145	0.0246
INF	4.9108	2.4808	1.981452	0.0495
INTR	-9.0608	1.2409	-0.732600	0.4650
EXPO	-9.7400	5.8856	-1.654378	0.0543
R-squared	0.985	F-statistic		188.41880
Adjusted R-squared	0.9848	Durbin Watson		0.5551

The results in (**tables 4.3 and 4.4**) revealed five regressors in the model, with 145 observations showing a significant probability value (0.000) of all independent indicators except one. The Heteroskedasticity test Breusch-Pagan-Godfrey result showed a Prob Chi-Square value (0.67) regardless of the outcome. If this p-value is lesser than 0.05, it has to be the case for both serial correlation and heterosdeskedasticty (Felsenstein & Churchill, 1996). These indicators tested the case of serial correlation in the model empirically, as the HAC test shows the same R-square (0. 98). The value of Durbin Watson stat (0.5521) is the same as before, led to the provision of autocorrelation. The same value in HAC & covariance (B k, Newey-W) also concluded the study's first objective, the results with the element of autocorrelation in the time series data. Results are similar to the finding of (Gujarati, 2011). This also covers the study's first objective, which investigates how autocorrelation affects the results. Furthermore, the second aim of the inquiry was to examine whether this has to be the situation where autocorrelation is pure autocorrelation that seems to be or the consequences of a mis-specified model in the research or collaboration that has led us to errors of heteroscedasticity, therefore, it is also established that this is the case of pure serial correlation which cover the second objective of the study (Yen & Cheng, 2021).

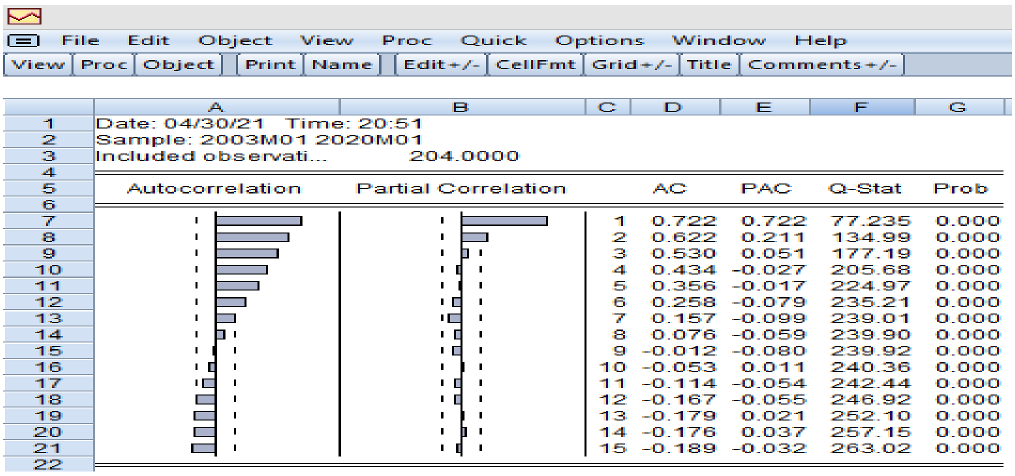


Figure 1: Autocorrelation test

From the above (figure 1), autocorrelation gives the test an indication of autocorrelation shown at the upper tier till the seventh value of AC, where it should be less than 0.05 and Q-stat should be more than 5% Baltagi (2021). The auto correlation coefficients versus time lag is called correlogram as you see here the horizontal axis is the time lag when it displays one at this point as YT minus one and this data shows the correlation between YT and YT minus one the second bar shows the correlation between YT and YT minus two so you continue like that until like 7 here we see an example of Carlo graph that contains auto correlations until like 7 let's see how we read this colorgram once again for example the auto correlation is the correlation between the date I'd period t and the data at period t minus 1 and has a positive auto correlation of 0.7 that means the data today and the data that yesterday I observed are highly correlated similarly the lag to auto correlation is the correlation between data a period and the data at period t minus 2 and it is 0.6 we see multiple bars like the first one and the second one exceeds the threshold so this is the upper limit as you see exceeds the threshold the thresholds are the horizontal lines and indicates that these auto correlations are statistically significant so if you see a bar above the threshold you're going to say that this correlation between these two is in fact significance and it is not zero they are related and time reluctant.

Table 4.5 The remedial measure to autocorrelation

Breusch-Godfrey Serial Correlation LM

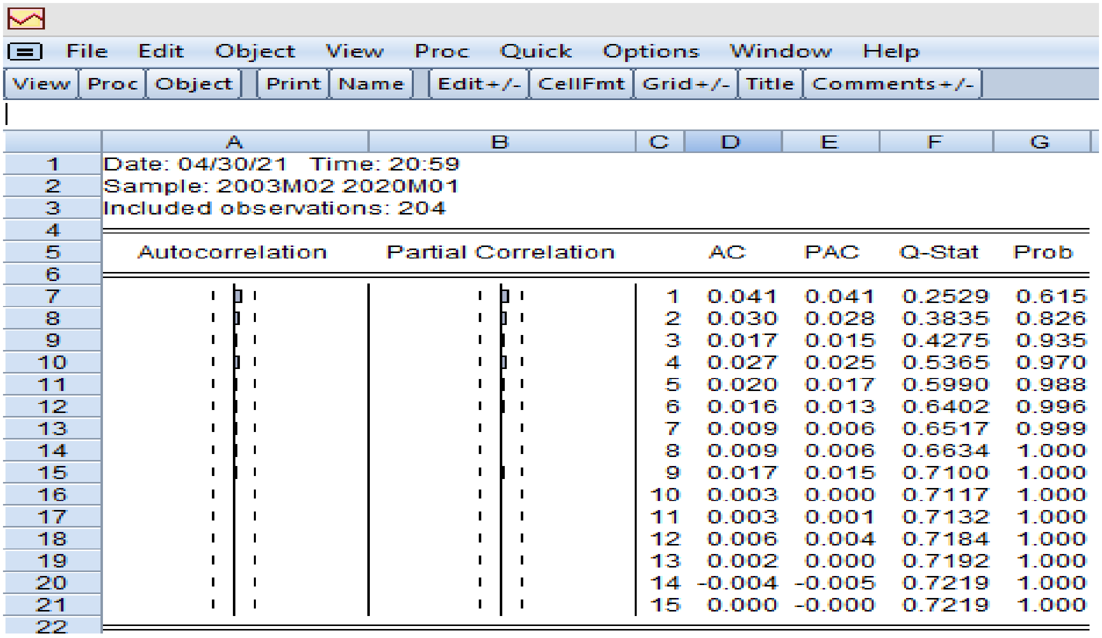
F-stat	182.8104	Prob. F(1,138)	0.00000
Obs R-sqd	82.62672	ProbChi-Square(1)	0.98000

Table 4.5.1 Dependent Variable: RESID

Remedial model				
Variable	Coefficient	Std. Error	t-Statistic	Prob.
C	1.1009	5.5909	0.197436	0.8438
EXM	0.0181	0.0138	1.96496	0.0480
SI	-5184.9	1447.9	-3.594449	0.0005
INF	-49989	1.4208	-2.352571	0.0424
INTR	-5.9308	4.9108	-1.206598	0.2297
EXPO	5.9081	3.3788	1.998623	0.0526
RESID(-1)	0.7874	0.0545	13.52074	0.0000
R-squared	0.569	F-statistic		30.41
Adjusted R-squared	0.519	Durbin Watson		1.967

The above (**table 4.5 & 4.5.1**) Breusch Godfrey test shows that the element of serial correlation is removed from the model by taking the first difference and applying the test, which efficiently diagnosed and effectively removed this problem. The above breusch G (table 5) of serial LM test eliminated the factor of pure correlation through this test where the p-value is (0.98) of Chi-square. Transforming the original model into the transformed model may break the chain of similar patterns from one-time period value transfers to the subsequent. Therefore, we try several transformations, such as the first-difference and generalized difference transformations, by Dropping the First Observation or dropping the second observation. The outcome from (**table 5.1**) revealed five regressors in the model, with 204 observations showing a significant probability value (0000), which explores that the actual result favors the research. Observing the value of Durbin Watson stat (1.967) led to no autocorrelation as this value must not be close to zero Vinod (1973). No autocorrelation existed in indicator Predictand which is REM.

Furthermore, the value of R/Sqd and AdjR/Sqd is (0.5699) and (0.5517), respectively, significantly reducing variance in the model. It also supports the study's first objective, the results with and without the element of autocorrelation in the time series data. The third objective of the research investigation is to examine how this problem will cause results and what remedial measures are effective in these circumstances.



Autocorrelation	Partial Correlation		AC	PAC	Q-Stat	Prob
		1	0.041	0.041	0.2529	0.615
		2	0.030	0.028	0.3835	0.826
		3	0.017	0.015	0.4275	0.935
		4	0.027	0.025	0.5365	0.970
		5	0.020	0.017	0.5990	0.988
		6	0.016	0.013	0.6402	0.996
		7	0.009	0.006	0.6517	0.999
		8	0.009	0.006	0.6634	1.000
		9	0.017	0.015	0.7100	1.000
		10	0.003	0.000	0.7117	1.000
		11	0.003	0.001	0.7132	1.000
		12	0.006	0.004	0.7184	1.000
		13	0.002	0.000	0.7192	1.000
		14	-0.004	-0.005	0.7219	1.000
		15	0.000	-0.000	0.7219	1.000

Figure 2: Test of the cross correlogram

From the above (figure 2), AC and Q-Stat gave the impression and established empirically that in the test of cross correlogram, there is no indication of autocorrelation shown at the upper-tier till the last lag as before. The value of AC 0.041is less than 5%, which clarifies no element of problem exists anymore in the model, and the values of Q-stat are more than 0.05, which ultimately claims the technique employed is effective for the removal of this severe problem naming autocorrelation according to the econometric assumption now we could say that estimation is BLUE.

Conculsion

From the above practical demonstration, we have concluded that scholars and academic statisticians must differentiate and identify the difference between error terms such as hero and a pure case of autocorrelation to generate a blue estimation. This paper has explored the difference between HAC and a pure case of autocorrelation to understand the problem; by properly understanding the problem, it becomes easy for the researcher to apply the required tools for removing autocorrelation in the time series data for unbiased results. Firstly, as shown above, in the tables, various detection tests such as Breusch Godfrey, LM, HAC, and newey west tests are employed to explain the error terns transformation and emphasize the results with the element of the problem. All the graphical, cross correlogram pictorials, and test analyses have indicated the problem of pure autocorrelation in the time series data (utilized). Proper detection and testing tools can remove this problem for better and correct forecasting. Secondly, the method and techniques employed in the research have shown the results without eliminating a single outlier from the data. The tests before and after have shown a significant difference in P-values, Errors, and coefficient

Policy implications for the economist

There should be a flawless understanding of the first, second and third order detection process to seek out the problem. With the help of these tests and tools, academic researchers can improvise the results. A distinctive literature exploration to be promoted to enlighten the difference between HAC and the case of pure autocorrelation in the model. The results will help understand the estimation unbiased procedures and aid in better consideration of this problem as a chain reaction of error terms. Academic scholars and statisticians can estimate forecasts correctly with this robust modeling in the future. Before and after autocorrelation, tests show a significant difference in P-values, errors, and coefficients. The estimations used will assist the scholars and policymakers on how error terms have played a significant role, referring to autocorrelation with and without the factor.

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