

Introduction to Econometrics
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Lecture 54

Relaxing the assumptions of CLRM-Autocorrelation and Heteroscedasticity Part - 5

So, welcome to our discussion of heteroscedasticity once again and if you recall yesterday in our last class we were discussing about Goldfeld and Quandt test for detecting heteroscedasticity. And then we also discussed about some of the major limitations of this heteroscedasticity detection by Goldfeld and Quandt test and the major limitation was that in Goldfeld and Quandt test you need to arrange your explanatory variables from smaller to the bigger ones.

That means if you have only one explanatory variable while it is quite easier to arrange your explanatory variable from small to big but when you have a large number of explanatory variables and you are not sure about which particular explanatory variable is creating heteroscedasticity problem then basically you need to repeat the same procedure of Goldfeld and Quandt test for all the explanatory variables which is quite time-consuming process.

Based on that difficulty econometricians have developed another test which is called Breusch-Pagan Godfrey test or in short BPG test. Before we go ahead with the BPG test if you recall yesterday, I said that all these tests based on which particular assumption you are making about your sigma square that means error variance.

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Heteroskedasticity

$\sigma_i^2 = f(x)$ $H_0: \text{Homoskedasticity}$

GQ: $\sigma_i^2 = \sigma^2 x_i^2$ $\frac{RSS_u/d_f}{RSS_l/d_f} \sim F$

Breusch-Pagan-Godfrey test (BPG)

Original model $\leftarrow y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki} + u_i$ $\sigma_i^2 = f(x)$

$= (\alpha_1 + \alpha_2 z_{1i} + \alpha_3 z_{2i} + \alpha_4 z_{3i} + \dots + \alpha_m z_{mi} + u_i)$

In all these models we assume that σ^2 is actually a function of your explanatory variable where x is basically explanatory variable, this is a function of x . And these different tests are developed based on which specific functional form you are assuming for $f(x)$.

So, in Goldfeld-Quandt test GQ test, you assume that σ^2 equals to some σ^2 into x^2 . So, that means σ^2 is basically an increasing function of x it is x^2 so that means as x increases σ^2 increases at an increasing rate.

How we have constructed the test statistic in Goldfeld and Quandt test if you recall? That was RSS_2 by its corresponding degrees of freedom and divided by RSS_1 by its corresponding degrees of freedom. What is RSS_2 ? RSS_2 is basically the RSS from the model wherein you are running a regression of y on x and x is from the second sample, you have arranged the data, you have arranged the x variables according to their magnitude.

So, second sample consists of the larger values of x and the first sample consists of the smaller values of x . So, obviously because of this particular assumption σ^2 equals to σ^2 into x^2 . RSS_2 should be quite higher than RSS_1 .

Now, this particular test will follow the F statistic. Now, larger the difference between RSS_2 and RSS_1 greater would be the value of F and greater would be the probability of rejecting your null hypothesis where null is basically homoscedasticity. So, you can reject the homoscedasticity assumption that was the procedure we discussed about in Goldfeld and Quandt test.

Now, today what we will do, we will discuss about Breusch-Pagan and Godfrey test, Breusch-Pagan and Godfrey, in short this is called BPG. So, here also what we assume? σ^2 is a function of x and what is the specific functional form they have assumed? They have assumed σ^2 equals to some $\alpha_1 + \alpha_2 z_1 + \alpha_3 z_2 + \alpha_4 z_3 + \dots + \alpha_m z_m + u_i$ that is the specific functional form they have assumed in Breusch-Pagan and Godfrey test.

And what is this z actually, let us say that your original model is y_i equals to $\beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki} + u_i$ this is your original model of interest. So, that means we are interested to see whether heteroscedasticity exists in this original model in this data set.

Now, this z basically, the z, the set of variable that consists z coming from all or some of your x variables, some of your x variables that is the assumption that you make. So, we assume that all or some of your x actually consist this z, z1 might be x1, z2 might be x2 like that, so all or some of your x is actually z, so you can write this equation as in terms of x also.

So, what you need to observe here, look at the way I have specifically mentioned the nature of f(x) here vis-a-vis in the context of Goldfeld and Quandt test, this is the procedure. Now, in Breusch-Pagan Godfrey test they have also given certain steps and I will now discuss about the tests.

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BP Test:

$$y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki} + u_i \dots \textcircled{1}$$

step 1: estimate model $\textcircled{1}$ and get the RSS

$$\hat{\sigma}_{ML}^2 = \frac{RSS}{n}$$

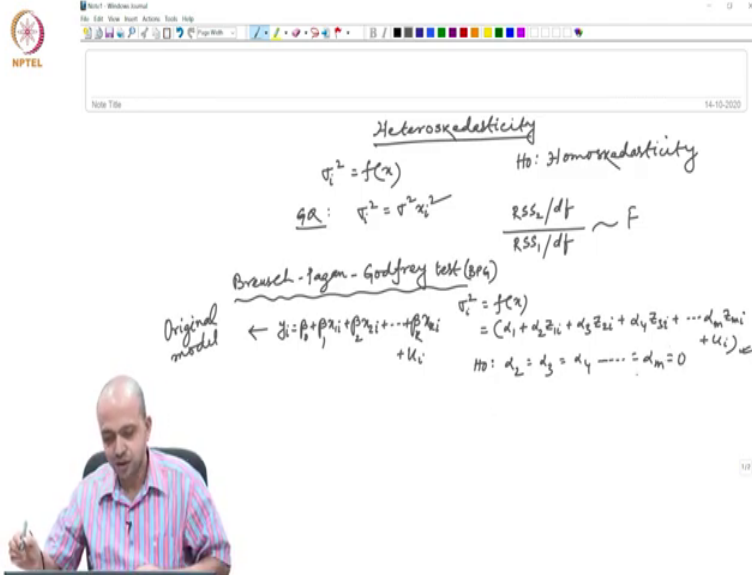
$$\left(\frac{RSS}{n-k} \right) = \frac{\hat{\sigma}_{OLS}^2}{\sigma_{OLS}^2}$$

step 2: $\frac{u_i}{\hat{\sigma}_{ML}^2} = \hat{u}_i$

step 3: $\hat{u}_i = \lambda_0 + \lambda_1 x_{1i} + \lambda_2 x_{2i} + \dots + \lambda_k x_{ki} + \epsilon_i \dots \textcircled{2}$
and collect ESS from $\textcircled{2}$ $H_0: \lambda_1 = \lambda_2 = \dots = \lambda_k = 0$

step 4: $\frac{1}{2} ESS \sim \chi_{df}^2 = (m-1)$ where m is the total number of parameters in the original model

$\chi_{cal}^2 > \chi_{tab}^2 \Rightarrow \text{reject } H_0$



So, this is BPG test. So, step 1 and your model is y_i equals to β_0 plus $\beta_1 x_{1i}$ plus $\beta_2 x_{2i}$ plus $\beta_3 x_{3i}$ plus $\beta_k x_{ki}$ plus u_i , this is your model. And what is your step 1? So, in step 1 they say that you estimate this model let us say from this is model 1, you estimate your model and then from this model estimate model 1 and get the RSS.

And from RSS what they are asking you to calculate some kind of let us say σ^2 which is basically nothing but RSS divided by n . Now, what is RSS by n ? RSS by n is actually if you recall that RSS by $n - k$ equals to we said that this is basically $\hat{\sigma}^2$ from that OLS model, that means if you divide the RSS by $n - k$ you will get the sample statistic of the σ^2 . σ^2 is the error variance which is unknown population parameter and the sample counterpart of σ^2 is basically $\hat{\sigma}^2$ which is coming from your OLS model that is RSS by $n - k$.

Here when I am doing RSS by n that is basically the estimate of σ^2 coming from the ml method or maximum likelihood method that is the difference. So, both $\hat{\sigma}^2$ and σ^2 , they are actually the sample statistic or sample counterpart of the true population parameter σ^2 which is unknown.

So, we are, since in presence of heteroscedasticity σ^2 , σ^2 is actually biased, σ^2 does not reflect the true σ^2 , we are trying to get $\hat{\sigma}^2$ from the maximum likelihood method and how we are defining this is basically RSS by n .

Then in step 2 they say that once you rectify your sigma square by sigma tilde square then what you generally need to do is you just divide your u_i hat square by sigma tilde square and define that as p . So, what I am doing? Since your error variance is disturbed in presence of heteroscedasticity look what I am doing, I am just correcting, I am just adjusting the u_i hat square by this new estimate of sigma square which is sigma tilde square and I am defining that as p . That is your step 2.

Then in step 3, you regress this p equals to all your explanatory variables that means you regress p equals to $\sum \lambda_0$ plus $\lambda_1 x_{1i}$ plus $\lambda_2 x_{2i}$ plus $\lambda_k x_{ki}$ plus ϵ_i . So, you have to run a regression of p on this. And what you have to do, you have to and collect the ESS from let us say this is model 2.

Then in step 4 basically they say that half of ESS follows a chi square distribution where degrees of freedom equals to m minus 1, where m is the total number of parameters in this original model. So, if the calculated F is greater than chi square tabulated then you reject your H_0 and what is our H_0 , that there is no heteroscedasticity. So, that means if you think about the logic or philosophy of all these tests then things become very clear to you.

Goldfeld-Quandt test was also based on two RSS- RSS_2 by RSS_1 . Why? Because we assumed that sigma square i equals to some sigma square multiplied by x_i square, so sigma square i is basically a increasing function of x , so that is why we divided the entire sample into two, one consist of smaller value, another consist of higher value and then we are taking RSS_2 divided by degrees of freedom divided by RSS_1 by its degrees of freedom.

So, that means this RSS_2 by degrees of freedom is nothing but sigma 2 hat square. And what is RSS_1 by its degrees of freedom? That is sigma 1 hat square. Same thing we are doing here. Here we are assuming that sigma square is a linear function of sum of all your explanatory variable that is all.

See if that is the case what we are trying to do, we are trying to adjust the error term of the original variable u_i with a proper estimate of sigma square and how do you get a proper estimate of sigma square? This is the way the traditional definition RSS by n minus k which is the definition of sigma square from the OLS model is not working here in presence of heteroscedasticity.

Instead of using that what we are doing, we are taking RSS by n , that is all. Then we are adjusting our u_i hat square by this newly estimated σ^2 and defining that as p . So, if at all this adjusted error term has something to do with your explanatory variable then obviously this p defined in this way should be explained by this parameter.

So, that means basically from this model I am testing this hypothesis $\lambda_1 = \lambda_2 = \dots = \lambda_k = 0$ or not. So from here what I am testing this is my test $\alpha_2 = \alpha_3 = \alpha_4 = \dots = \alpha_m = 0$. So, if this is rejected then that means all these parameters are actually not equal to 0 that means σ^2 is something to do with the explanatory variable, but it is not rejected that means these are all 0- σ^2 equals to only α you have constant error variance that is the logic.

So, we should understand the logic of this test and logic is basically we are trying to modify some way or the other the RSS term and then we are constructing the test statistic based on that, this is the RSS modified, then we are defining p , p we are regressing, then we are collecting the ESS dividing it by 2 and that follows this chi square distribution with $m - 1$ degrees of freedom, where m is the total number of parameters to be estimated from the original model, this is the procedure of Breusch-Pagan and Godfrey test or BPG test. Now, what we will do, we will take the same data set what we are using yesterday and then we will see how to demonstrate this particular test in stata.

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The screenshot shows the Stata software interface. The command window contains the command `reg consumption income`. The main window displays the Stata startup screen, including the Stata logo, version 16.0, and license information for NPTEL. The Variables window on the right shows the variables `consumption` and `income`.

The screenshot shows the Stata software interface displaying the output of the regression model. The command window shows the command `reg consumption income`. The main window displays the regression results, including the ANOVA table and the coefficient table.

Source	SS	df	MS	Number of obs = 30
Model	41886.7134	1	41886.7134	F(1, 28) = 496.72
Residual	2361.15325	28	84.3260918	Prob > F = 0.0000
Total	44247.8667	29	1525.78851	R-squared = 0.9466
				Adj R-squared = 0.9447
				Root MSE = 9.183

	coef.	Std. Err.	t	P> t	[95% Conf. Interval]
consumption					
income	-0.377846	0.0286167	22.29	0.000	-0.579366 -0.1960311
_cons	9.290307	5.231386	1.78	0.087	-1.4257 20.00632

So, I have already imported the data, so first what you have to do, you have to run your original model where original model is `reg consumption income`, this is your original regression. And then from here what you have to do, you have to collect the RSS and you have to divide by RSS by n to get σ^2 .

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Single-user Stata perpetual license:
Serial number: 48166221548
Licensed to: NPTEL

Notes:
1. Unicode is supported; see help unicode_advice.
2. Maximum number of variables is set to 5000; see help set_maxvar.

*(4 variables, 30 observations pasted into data editor)

```

. reg consumption income

```

Source	SS	df	MS	Number of obs	=	30
Model	41886.7134	1	41886.7134	F(1, 28)	=	496.72
Residual	2361.15325	28	84.3269018	Prob > F	=	0.0000
				R-squared	=	0.9466
				Adj R-squared	=	0.9447
Total	44247.8667	29	1525.78951	Root MSE	=	9.183

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]
income	-.6377846	.0286167	-22.29	0.000	-.791566 -0.964031
_cons	9.290307	5.231306	1.78	0.087	-1.4257 20.00632

```

. gen sigmaq=2361.15/30

```

Now, what I will do I will define the sigma tilde i square I am simply writing sigma square sigma sq equals to, what is your RSS here? RSS look 2, 3, 6, 1 equals to 2, 3, 6, 1, 0.15 divided by n and what is your n here, 30.

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```

. reg consumption income
. gen sigmaq=2361.15/30
. predict u, resid
. gen usq=u^2

```

Then what you also do you predict, predict u comma residual and then you generate the square of u, gen u square usq equals to u, this is u square. So, I have generated sigma tilde square, I have generated u hat square. Then how do you define your p?

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The screenshot shows the Stata command window with the following commands and results:

```

1. reg consumption income
2. gen sigmaq=2361.15/30
3. predict u, resid
4. gen usq=u^2
5. gen p=usq/sigmaq

```

The regression output for `reg consumption income` is as follows:

Source	SS	df	MS	Number of obs = 30
Model	41886.7134	1	41886.7134	F(1, 28) = 496.72
Residual	2361.15325	28	84.326918	Prob > F = 0.0000
Total	44247.8667	29	1525.78951	R-squared = 0.9467
				Adj R-squared = 0.9417
				Root MSE = 9.183

The coefficient table for the regression is:

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
income	.6377846	.0286167	22.29	0.000	.579166	.6964031
_cons	9.290307	5.231386	1.78	0.087	-1.4257	20.00632

The command window also shows the following commands:

```

.gen sigmaq=2361.15/30
.predict u, resid
.gen usq=u^2
.gen p=usq/sigmaq

```

The p is basically $\text{gen } p \text{ equals to } \frac{u^2}{\sigma^2}$ that is how I have defined my p, so \hat{u}^2 divided by your sigma, sigma square, sigma tilde square so this is your p.

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The screenshot shows the Stata command window with the following commands and results:

```

1. reg consumption income
2. gen sigmaq=2361.15/30
3. predict u, resid
4. gen usq=u^2
5. gen p=usq/sigmaq
6. reg p income

```

The regression output for `reg p income` is as follows:

Source	SS	df	MS	Number of obs = 30
Model	10.420895	1	10.420895	F(1, 28) = 5.87
Residual	48.910098	28	1.7467974	Prob > F = 0.0211
Total	59.330994	29	2.0459101	R-squared = 0.1757
				Adj R-squared = 0.1463
				Root MSE = 1.3217

The coefficient table for the regression is:

	Coef.	Std. Err.	t	P> t	[95% Conf. Interval]	
income	.0100632	.0041187	2.44	0.021	.0016265	.0184999
_cons	-.7426146	.7529284	-0.99	0.332	-2.284918	.7996892

The command window also shows the following commands:

```

.gen sigmaq=2361.15/30
.predict u, resid
.gen usq=u^2
.gen p=usq/sigmaq
.reg p income

```

And then you regress p, p on your explanatory variable you have only one explanatory variable which is income. And from this model you have to take your ESS which is 10.42.

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BP Test: $y_i = \beta_0 + \beta_1 x_{1i} + \beta_2 x_{2i} + \dots + \beta_k x_{ki} + u_i \dots \textcircled{1}$

step 1: estimate model $\textcircled{1}$ and get the RSS
 $\frac{\sum u_i^2}{n} = \frac{RSS}{n}$ $\left(\frac{RSS}{n-k}\right) = \frac{\sum u_i^2}{\text{d.o.f}}$

step 2: $\frac{\sum u_i^2}{n} = \hat{\sigma}^2$

step 3: $\hat{\beta} = \lambda_0 + \lambda_1 x_{1i} + \lambda_2 x_{2i} + \dots + \lambda_k x_{ki} + \epsilon_i \dots \textcircled{2}$
 and collect ESS from $\textcircled{2}$ $H_0: \lambda_1 = \lambda_2 = \dots = \lambda_k = 0$

step 4: $\frac{1}{2} ESS \sim \chi^2_{df=(m-1)}$ where m is the total number of parameters in the original model

$\chi^2_{\text{cal}} > \chi^2_{\text{tab}} \Rightarrow \text{reject } H_0$
 $\chi^2_{\text{cal}} = \frac{1}{2}(10.42) = 5.21$
 $\chi^2_{\text{tab}}(5\%) = 3.23$

So, if it is 10.42 then if you look at from here if it is 10.42 that means your chi square calculated should be half into 10.42. so which is nothing but 5.21 so this is your calculated chi square. Now, what is the tabulated value?

Chi square tabulated at 5 percent level of significance equals to something around 3.23 or something, you can check the chi square value with m degrees of freedom. What is m here? m equals to 2, so degrees of freedom would be 1, this chi square tabulated would be 1 degrees of freedom because in your original model you have only 2 parameters, income coefficient and the constant term, this is 3.2. So, you can reject your null that means this implies that chi square calculated is greater than chi square tabulated at 5 percent significance. So, at 5 percent level of significance you can say that your data is suffering from heteroscedasticity problem.