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Influence of data vintage on quantification of expectations

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Abstract

Importance of acknowledging data revisions – that is, corrections published after the initial announcement was made – has been repeatedly stressed in current economic literature. In this paper, I propose to test whether including information on data revisions infuences results of regression quantification procedures. Empirical analysis leads to the conclusion that end-of-sample data appears better suited for quantification of business tendency survey data on volume index of industrial production sold.

Keywords: end-of-sample (EOS) data, real time (RTV) data, data revisions, survey data, production index, expectations, quantification, regresssion method

JEL: C82, C83, D84

1. Introduction

In this paper, I propose to test whether data vintage influences results of quantification procedures used to convert quantitative questionnaire data into qualitative time series. While quantification procedures are fairly commonly used in survey data studies, as they allow formal analysis of survey data dynamics and comparisons with official statistics, vintage of data on which quantification models are based is generally ignored.

The importance of taking data revisions into account has been highlighted in my previous paper (Tomczyk 2013) in which I present review of literature and databases available for the purposes of real time analysis. Recent papers generally confirm that data revisions tend to be systematic and significant, and that data vintage should be taken into account when evaluating results of empirical economic research. Croushore (2012) shows that results of analyses of bias in survey forecasts of output growth and inflation heavily depend on vintage of data used to evaluate forecasts. Abo-Zaid (2013) demonstrates that first releases of data on net job creation in US can be misleading, and subsequent revisions introduce significant corrections. Arnold (2013) shows that initial announcements on several US and European macroeconomic indicators are considerably revised, in some cases systematically, influencing evaluation of forecast errors. Franses (2013) shows that data revisions may introduce periodicity (that is, seasonally varying heteroscedasticity and serial correlation) into time series, and therefore should be carefully analyzed particularly when seasonally adjusted variables are used. Syczewska (2013) analyses influence of corrections and updates in yearly macroeconomic data available in the Eurostat AMECO database on results of econometric studies. She compares AMECO and Polish Central Statistical Office data and finds differences between various sources of macroeconomic data as well as significant revisions in successive editions which lead to changes in evaluation of quality of macroeconomic forecasts.

In contrast to majority of the texts published so far, based on yearly or quarterly macroeconomic indicators, in this paper I focus on data vintage issues pertaining to monthly data collected by the means of business tendency surveys and reported in monthly Statistical Bulletins of Polish Central Statistical Office. As far as I am aware, data revisions have not been taken into account when quantifying survey data or analyzing properties of expectations expressed in qualitative surveys in Poland.

2. Revisions in monthly Central Statistical Office data

There are several reasons for introducing data revisions in statistical reporting; they have been defined and described in Tomczyk (2013). All authors of papers referenced there, however, consider macroeconomic indicators measured with yearly or quarterly frequency, and do not refer to less aggregated (i.e. monthly) data.

Polish Central Statistical Office publishes hundreds of time series in its monthly Statistical Bulletins. In several places, data revisions are mentioned explicitly. A standard formula is used in all publications: “Some figures are provisional and may be subject to revision in next editions of the Statistical Bulletin. Such revised data will be marked with sign *” (see for example Statistical Bulletin No 11/2013, General Notes, p. 5, point 16). Furthermore, like most statistical reporting agencies of EU countries, CSO re-calculates time series every five years to account for methodological changes, and appropriate reminder is duly provided in methodological notes to the Bulletins. In comments to some tables (see for example Statistical Bulletin No 11/2013, Table 1 [Main indicators], p. 44 and 51) we learn that “Corrections made by reporting entities were included in cumulative data” but no explanation is provided as to how big these corrections were and whether they had systematic character or not.

Four of the monthly variables published by CSO have been previously compared with their equivalents collected through business tendency surveys by the Research Institute for the Economic Development (RIED) of the Warsaw School of Economics, that is, production, prices, employment and general business conditions (see Tomczyk 2008). Below I briefly describe revisions to these series introduced in the past two decades. To summarize, the only variable which exhibits regular – albeit small – revisions is volume index of production sold, and this variable is the subject of empirical analysis in sections 3 and 4.

2.1. Production

Analyses of industrial production are usually based on volume index of production sold in manufacturing. The only systematic data revisions in the past two decades were due to changes of base period for the index:

- from January 2004, average monthly industrial production of 2000 = 100 (before 2004, average monthly industrial production of 1995 = 100),
- from January 2009, average monthly industrial production of 2005 = 100,
- from January 2013, average monthly industrial production of 2010 = 100.

CSO warns that “The calculation of other dynamics of production (e.g., previous month=100) on the basis presented in the table is not advisable.” (see notes to Table 52, „Volume index of sold production of industry”, Statistical Bulletin No 11/2013, p. 159).

Apart from these systematic revisions, frequent corrections of last month’s value of production index can be observed in CSO data. Corrections are small in size but regular and will be analyzed in sections 3 and 4.

2.2. Prices

Analyses of producers’ prices are typically based on price indices of industrial production sold (often in manufacturing only, excluding other sectors), in two versions: with respect to corresponding period of previous year, and compared to previous month. Between 2005 and 2014, no revisions have been introduced other than change of base period in January 2009.

2.3. Employment

Analyses of employment numbers are usually based on data on average paid employment in enterprise sector. The only revision between 2005 and 2014 has been introduced in January 2009 to comply with the Polish Classification of Activities (PKD 2007), compiled on the basis of Statistical Classification of Economic Activities in the European Community. “PKD 2007 was introduced on 1st January 2008 by the decree of Council of Ministers dated 24 December 2007 (Journal of Laws No. 251, item 1885) to replace the formerly applied PKD 2004. (…) Starting with the Statistical Bulletin No. 1/2009, the current data is published according to the PKD 2007. Data for previous periods are also converted according to this classification." (Statistical Bulletin No 1/2009, General Notes, p. 6). Apart from this one-time revision, no corrections were introduced in the past two decades.

2.4. Business conditions

CSO publishes data on business tendency indicators (BTIs) in three time series: indicator of the general business tendency climate, BTI diagnosis and BTI forecast, all presented in seasonally adjusted and unadjusted versions and across subsectors. Full set of data on these indicators available from February 2009. Only a few minor corrections have been introduced between 2005 and 2014. For example, values of indicator of the general business tendency climate; manufacturing; seasonally unadjusted has changed in November 2007 (from 15.5 to 19.5) and in March 2008 (from 21.5 to 23.0). Two remaining business conditions series, BTI diagnosis and BTI forecast, have not been revised in the past two decades.

3. Description of data

To analyze influence of data vintage on results of quantification procedures for index of industrial production, two sources of data are needed: official statistics (in this case, monthly data supplied by CSO in Statistical Bulletins) and qualitative data provided by survey respondents. Both data sources are briefly described in this section.

3.1. Volume index of industrial production sold

Volume index of sold production published by CSO is (occasionally) revised one month after the initial release, and there are no further updates. Structure of data revisions in volume index of production is shown in Table 1. Each column represents vintage of data and contains data that would have been available at a given moment. Last cell in each column (shaded grey) is the initial release of a value corresponding to a given date. The history of data revisions are represented by rows; in each row, from left to right, corrections are shown (if data are revised). Data revisions is marked in bold.

Table 1. Revisions of volume index of industrial production sold (in manufacturing) for June 2013 – December 2013

	June 2013	July 2013	August 2013	September 2013	October 2013	November 2013	December 2013
June 2013	114.6	**114.3**	114.3	114.3	114.3	114.3	114.3
July 2013		115.6	115.6	115.6	115.6	115.6	115.6
August 2013			109.9	109.9	109.9	109.9	109.9
September 2013				121.5	121.5	121.5	121.5
October 2013					127.4	**127.6**	127.6
November 2013						118.4	118.4
December 2013							103.5

Source: CSO Bulletins

From Table 1 it is clear that revisions are regular but small. However, month-to-month changes in expectations expressed in business tendency surveys also tend to be small. Quantification procedures (particularly regression methods that directly compare survey and CSO data; see section 4) may therefore be sensitive even to minor corrections in input data.

In section 4, results of quantification procedures are reported for volume index of production sold from January 2009 to April 2014 (64 observations) for two data vintages:

- RTV (real time data): initial release available in a given month,
- EOS (end-of-sample): final data which became available one month after the initial announcement.

In Table 2, summary statistics for both data vintages are provided. There are only minor differences between them, suggesting that data vintage may not be of tangible importance for further empirical analysis of volume index of industrial production sold.

Table 2. Summary statistics of revisions in volume index of industrial production sold

	Initial release (RTV)	Final release (EOS)
Mean	136.06	135.42
Standard deviation	19.59	20.19
Minimum	100.10	95.60
Maximum	172.40	172.60

Source: own calculations on the basis of Central Statistical Office data

In Table 3, structure of revisions in volume index of industrial production sold is summarized.

Table 3. Direction of revisions in volume index of industrial production

Direction of revision	Percentage in sample
Initial value larger than final value	33%
Initial value smaller than final value	39%
No revision	28%

Source: own calculations on the basis of Central Statistical Office data

Results reported in Table 3 suggest that revisions in volume index of industrial production sold may be unbiased (there are about as many downward and upward corrections). However, more detailed analysis of properties of revisions is called for, as is planned as the next step in empirical analysis of revisions in volume index of industrial production sold (see section 5).

3.2. Reported and expected changes in industrial production

Production expectations and subjective assessments are taken from the monthly business tendency survey administered by the Research Institute for Economic Development (RIED) at the Warsaw School of Economics. Each survey question asks respondents to evaluate both current situation (as compared to last month) and expectations for the next 3 – 4 months by assigning them to one of three categories: increase / improvement, no change, or decrease / decline (see Appendix 1). Aggregated survey results are regularly published and commented on in RIED bulletins: each month, a number of respondents is given, along with a percentage of respondents who observed increase / no change /

decline and who expect increase / no change / decline in a given area of economic activity, along with a balance statistic calculated as a difference between percentage of 'optimists' (those who judge current situation favorably or predict improvement) and 'pessimists' (those who evaluate present situation unfavorably or predict decline).

As noted above, respondents of RIED business surveys are asked for their expectations for the next 3 – 4 months. Previous studies based on RIED survey data (see Tomczyk 2008) show that expectations series defined for three and four month horizons exhibit only minor differences. Three-month forecast horizon (k = 3) is therefore used in this paper.

RIED business survey data is not revised after the initial announcement.

Let us define the following:

A_t^1 – percentage of respondents who observed increase between t and t + 1,

A_t^2 – percentage of respondents who observed no change between t and t + 1,

A_t^3 – percentage of respondents who observed decrease between t and t + 1,

P_t^1 – percentage of respondents who expect increase between t and t + 3,

P_t^2 – percentage of respondents who expect no change between t and t + 3,

P_t^3 – percentage of respondents who expect decrease between t and t + 3.

Balance statistic calculated for observed changes:

$$BA_t = A_t^1 - A_t^3$$

and for expectations:

$$BP_t = P_t^1 - P_t^3$$

remain the simplest method of quantification – that is, converting qualitative business survey data into quantitative time series. More sophisticated procedures can be grouped into probabilistic and regressive quantification methods (for a concise review of basic quantification methods and their modifications, see Pesaran, 1989). None of the two basic quantification approaches proved to be generally superior; their performance depends on several factors, including dynamics of forecasted variables and time horizon considered. In this paper, I focus on the regression method which is recommended for quantifying variables over which survey respondents exercise at least limited control (see Nardo, 2003) even though quantification models are not meant to reflect a causal relationship. In section 4, two versions of regression method are used to compare results for real time and end-of-sample data vintages.

4. Results of quantification procedures for RTV and EOS data

For the purpose of quantifying RIED data on level of production, I employ two versions of the regression method, introduced by O. Anderson and D. G. Thomas, respectively. In Anderson's model, the following equation is estimated:

$$ {}_{t}x_{t+1} = \alpha \cdot A_t^1 + \beta \cdot A_t^3 + \nu_t \,, \tag{1} $$

where ${}_{t}x_{t+1}$ describes relative changes in value of variable x noted in official statistic between t and $t + 1$. Assuming that the same relationship holds true for expectations reported in surveys, and that error term in equation (1) meets standard OLS assumptions, parameters α and β are estimated, and quantitative measure of expectations is constructed on the basis of the following equation:

$$ {}_{t}\widehat{x}_{t+1} = \widehat{\alpha} \cdot P_t^1 + \widehat{\beta} \cdot P_t^3 \,, \tag{2} $$

where $\hat{\alpha}$ and $\hat{\beta}$ are OLS-estimators of (1) and reflect average change in variable ${}_{t}x_{t+1}$ for respondents expecting, respectively, increase and decrease of dependent variable.

A modification of the general Anderson model was proposed by D. G. Thomas in 1995 to allow for the special case in which normal or typical situation that respondents compare their current situation to includes a certain growth rate, making downward corrections more essential than upward:

$$ {}_{t}x_{t+1} = \gamma + \delta \cdot A_t^3 + \xi_t \,, \tag{3} $$

where $\delta < 0$, and constant γ is interpreted as typical growth rate. Thomas' quantitative measure of expectations is given by the formula

$$ {}_{t}\widehat{x}_{t+1} = \widehat{\gamma} + \widehat{\delta} \cdot P_t^3 \,, \tag{4} $$

where $\hat{\gamma}$ and $\hat{\delta}$ are estimates obtained on the basis of (3). Thomas's model reflects the assumption that behavior of economic agents depends on growth rate of a variable (usually production or prices – hence applicability for volume index of production) that the enterprise typically observes, and limits the degree of multicollinearity which often emerges in Anderson's model (1). Additionally, HAC standard errors are usually used to account for possible serial correlation and/or heteroskedasticity of the error term in equations (1) and (3).

To address the main issue of this paper – that is, sensitivity of quantification procedures to data vintage – dependent variable in quantification models (1) and (3) must be defined carefully. It may be based on either RTV or EOS data. In case of regression methods, final (EOS) data should probably be used as assessments of survey respondents are most likely aimed at final (revised) and not initial numbers. In case of probabilistic methods, selection of data vintage should probably depend on formulation of a survey question; its wording may suggest whether initial or final (revised) value should be used.[1] However, empirical analysis of whether RTV or EOS data seem to be reflected in RIED questionnaires has not been attempted so far.

In case of real time data (RTV), dependent variable in regression quantification models (that is, changes in volume of industrial production) is defined on the basis of volume index of industrial production sold available in real time, IP_t^{RTV}:

$$P_t^{RTV} = \frac{IP_t^{RTV}}{IP_{t-1}^{RTV}} - 1, \qquad t = 1, ..., 63. \tag{5}$$

Variable $(P_t^{RTV} \cdot 100)$ is interpreted as percentage change in volume of industrial production as compared to last month.

For final end-of-sample (EOS) data, dependent variable in regression quantification models is defined on the basis of the final announcement of volume index of industrial production sold, IP_t^{EOS}:

$$P_t^{EOS} = \frac{IP_t^{EOS}}{IP_{t-1}^{EOS}} - 1, \qquad t = 1, ..., 63. \tag{6}$$

[1] For this insight, I am grateful to Ms Ewa Stanisławska, reviewer of my previous paper.

One final concern is the change of base period for volume index of industrial production in January 2013. Since for the twelve months of 2012 there are both series available (that is, one relative to the average monthly industrial production of 2005 and another relative to the average monthly industrial production of 2010), a linear regression model was estimated to express data for 2013 in the terms of 2005 base period. Values of P_t^{RTV} and P_t^{EOS} for January 2013 have been recalculated to express relative change with respect to December 2012 correctly. Since relative changes are used to define dependent variables (5) and (6) in quantification equations, this is the only correction needed to assure that series are consistent across the entire sample.

Tables 4 and 5 present results of quantification procedures obtained with gretl software for dependent variables P_t^{RTV} and P_t^{EOS}. All quantification models are estimated by OLS with HAC standard errors to account for possible serial correlation of the error term (due to inertia often observed in expectations series) and heteroskedasticity (likely to result from learning patterns imbedded in expectations formation processes). Detailed estimation results are presented in Appendix 2 (Anderson' model) and Appendix 3 (Thomas' model).

Table 4. Anderson's model (1) with HAC standard errors

	RTV	**EOS**
$\hat{\alpha}$	0.1313	0.0626
$\hat{\beta}$	-0.1040	-0.0211
centered R^2	0.0358	0.0048
AIC	-131.5615	-139.1168
RESET p-value	0.0449	0.1060

Source: own calculations

Table 5. Thomas' model (3) with HAC standard errors

	RTV	EOS
$\hat{\gamma}$	0.0627	0.0261
$\hat{\delta}$	-0.2087	-0.0582
R^2	0.0350	0.0032
AIC	-131.7110	-139.0027
RESET *p*-value	0.0796	0.2492

Source: own calculations

Interpretation of results – using the example of estimates obtained through Anderson's model (1) with end-of-sample dependent variable P_t^{EOS} – is the following: in enterprises that within last month noted increase in production, average increase amounted to 6.26%; on the other hand, in enterprises that within last month noted decrease in production, average decrease was equal to 2.11%. All the remaining results presented in Tables 4 and 5 are interpreted similarly. From the assumption that these estimates hold also for expectations of respondents it follows that in enterprises that express expectations that production will increase in the following 3 months, production will in fact increase by, on average, 6.26%; in enterprises that express expectations that production will decrease in the following 3 months, production will decrease by, on average, 2.11%. One-month observed changes and three-month expectations are therefore described by an equation of the same regression parameters. This simplification constitutes a significant weakness of regression method, shared by all commonly used quantification methods. What is more, relationship between official data and subjective assessments may not be identical to the functional form of expectations formation process for survey respondents. This limitation can only be verified with individual data on survey respondents, and has not been attempted for RIED data so far due to problems of data availability.

For both data vintages and both quantification models, all explanatory variables exhibit correct signs. None of the explanatory variables, however, are significant at the 5% significance level. Moreover, sizes of estimates obtained for real time dependent variable are much higher than observed in previous research, and appear unlikely. It seems doubtful, for example, that average decrease in production in enterprises reporting reduced production amounts to as high as 20.87% (as shown by Thomas' model) or that increase in production in firms announcing production boost reaches 13.13% (in case of Anderson's model).

RESET test allows to accept functional form of three quantification models as correct; only in case of Anderson's model with real time dependent variable, null hypothesis of correct specification is rejected at the 5% significance level. However, coefficients of determination remain disappointing in all of the quantification models.

To summarize, comparison of regression quantification models across data vintages suggests that end-of-sample data provide results more reliable from the economic point of view but hardly satisfactory statistically, taking into account low coefficients of determination and insignificant explanatory variables in quantification models.

5. Conclusions and directions for future research

This paper compares results of regression quantification procedures of volume index of industrial production sold for two data vintages: real time and end-of-sample. Central Statistical Office data on production index is subject to frequent revisions, albeit small in absolute values. Comparison of estimates of quantification models across data vintages suggests that use of end-of-sample data leads to economically dependable conclusions and seems superior to use of real time data for this purpose. On the other hand, all quantification models exhibit low coefficients of determination and statistically insignificant explanatory variables. Overall, none of the models provide satisfactory estimation results but end-of-sample data appears better suited to quantification of RIED business tendency survey data on volume index of industrial production sold.

There are several directions of future research worth pursuing. First, analyses of properties of expectations time series (including unbiasedness and orthogonality of expectations errors to available information) can be conducted and compared for two data vintages: real time and end-of-sample. Qualitative expectations series can be determined on the basis of equations (2) and (4) for both data vintages, and their properties analyzed. This research project is already under way; initial results suggest that there are only minor differences in expectations series performance across data vintages.

Second, it is possible that use of real time or end-of-sample data depends on phase of the business cycle in Poland. For example, Arnold (2013) finds that recessions and periods of volatile stock market influence the tendency of forecasters to predict either the initial release or the final value of an economic variable. However, this line of research will require long time series of monthly frequency.

Third, there are several econometric issues worth considering with respect to data vintage and testing economic hypotheses. McCracken and Clark (2007) show that data vintage influences asymptotic distributions of tests statistics, and propose modifications reflecting noisy data revisions. Campos and Reggio (2013) prove that measurement errors, including data revisions, introduce inconsistency in Instrumental Variables estimators. These issues have not been so far taken into consideration when analyzing revisions of Polish economic data.

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Appendix 1. Monthly RIED questionnaire in industry

		Observed within last month	Expected for next 3 – 4 months
01	Level of production (value or physical units)	up unchanged down	will increase will remain unchanged will decrease
02	Level of orders	up normal down	will increase will remain normal will decrease
03	Level of export orders	up normal down not applicable	will increase will remain normal will decrease not applicable
04	Stocks of finished goods	up unchanged down	will increase will remain unchanged will decrease
05	Prices of goods produced	up unchanged down	will increase will remain unchanged will decrease
06	Level of employment	up unchanged down	will increase will remain unchanged will decrease
07	Financial standing	improved unchanged deteriorated	will improve will remain unchanged will deteriorate
08	General situation of the economy regardless of situation in your sector and enterprise	improved unchanged deteriorated	will improve will remain unchanged will deteriorate

Source: the RIED database

Appendix 2. Estimation results: Anderson's model

Dependent variable: P_t^{RTV}

OLS, using observations 2009:02-2014:04 (T = 63)
HAC standard errors, bandwidth 2 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
A1	0.13133	0.105414	1.2459	0.21758
A3	-0.10398	0.116739	-0.8907	0.37659

Mean dependent var	0.004767	S.D. dependent var	0.084567
Sum squared resid	0.428909	S.E. of regression	0.083853
R-squared	0.035783	Adjusted R-squared	0.019976
F(2, 61)	1.566841	P-value(F)	0.216986
Log-likelihood	67.78073	Akaike criterion	-131.5615
Schwarz criterion	-127.2752	Hannan-Quinn	-129.8757
rho	-0.058067	Durbin-Watson	2.096589

RESET test for specification -
Test statistic: F(2, 59) = 3.27358
with p-value = P(F(2, 59) > 3.27358) = 0.0448534

Dependent variable: P_t^{EOS}

OLS, using observations 2009:02-2014:04 (T = 63)
HAC standard errors, bandwidth 2 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
A1	0.0626333	0.0749513	0.8357	0.40661
A3	-0.0210574	0.0779536	-0.2701	0.78797

Mean dependent var	0.009934	S.D. dependent var	0.078528
Sum squared resid	0.380436	S.E. of regression	0.078972
R-squared	0.020877	Adjusted R-squared	0.004826
F(2, 61)	1.489779	P-value(F)	0.233508
Log-likelihood	71.55841	Akaike criterion	-139.1168
Schwarz criterion	-134.8306	Hannan-Quinn	-137.4310
rho	-0.198998	Durbin-Watson	2.389193

RESET test for specification -
Test statistic: F(2, 59) = 2.33405
with p-value = P(F(2, 59) > 2.33405) = 0.105788

Appendix 3. Estimation results: Thomas' model

Dependent variable: P_t^{RTV}

OLS, using observations 2009:02-2014:04 (T = 63)
HAC standard errors, bandwidth 2 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
const	0.062721	0.052486	1.1950	0.23671
A3	-0.208729	0.207764	-1.0046	0.31904

Mean dependent var	0.004767	S.D. dependent var	0.084567
Sum squared resid	0.427892	S.E. of regression	0.083753
R-squared	0.034962	Adjusted R-squared	0.019142
F(1, 61)	1.009308	P-value(F)	0.319037
Log-likelihood	67.85548	Akaike criterion	-131.7110
Schwarz criterion	-127.4247	Hannan-Quinn	-130.0252
rho	-0.051308	Durbin-Watson	2.081506

RESET test for specification -
Test statistic: F(2, 59) = 2.6422
with p-value = P(F(2, 59) > 2.6422) = 0.0796192

Dependent variable: P_t^{EOS}

OLS, using observations 2009:02-2014:04 (T = 63)
HAC standard errors, bandwidth 2 (Bartlett kernel)

	Coefficient	*Std. Error*	*t-ratio*	*p-value*
const	0.0260884	0.035659	0.7316	0.46721
A3	-0.0581812	0.135673	-0.4288	0.66956

Mean dependent var	0.009934	S.D. dependent var	0.078528
Sum squared resid	0.381125	S.E. of regression	0.079044
R-squared	0.003150	Adjusted R-squared	-0.013192
F(1, 61)	0.183898	P-value(F)	0.669555
Log-likelihood	71.50136	Akaike criterion	-139.0027
Schwarz criterion	-134.7165	Hannan-Quinn	-137.3169
rho	-0.193768	Durbin-Watson	2.379556

RESET test for specification -
Null hypothesis: specification is adequate
Test statistic: F(2, 59) = 1.42288
with p-value = P(F(2, 59) > 1.42288) = 0.249166