QUANTITATIVE METHODS IN ECONOMICS
Vol. XVI, No. 2, 2015, pp. 123 – 132

DATA VINTAGE IN TESTING PROPERTIES OF EXPECTATIONS

Emilia Tomczyk
Institute of Econometrics, SGH Warsaw School of Economics
e-mail: Emilia.Tomczyk@sgh.waw.pl

Abstract: Results of quantification procedures and properties of expectations series obtained for two data vintages are described. Volume index of production sold in manufacturing is defined for end-of-sample and real time data, and evaluated against expectations expressed in business tendency surveys. Empirical analysis confirms that while there are only minor differences in quantification results with respect to data vintage, properties of expectations time series obtained on their basis do diverge.

Keywords: end-of-sample (EoS) data, real time (RTV) data, data revisions, quantification procedures, expectations, unbiasedness, orthogonality

INTRODUCTION

Testing properties of economic expectations series constitutes a challenge for many reasons, among them those related to observing and measuring expectations, reliability of survey data, and selection of appropriate statistic and econometric methods for the purposes of empirical analysis. In this paper, I propose to address one of the issues related to quality of data employed to describe and evaluate expectations processes, that is, the subject of data revisions and data vintages.

Data revision is defined as an adjustment introduced after initial announcement had been published. End-of-sample (EoS) data is usually described, following Koenig et al. [2003], as data provided in the most recent announcement. Real time values (RTV) are initial numbers, available to economic agents in real time and (frequently) subject to revisions. The date when a particular dataset was made available is termed "vintage" of that data series. For details on definitions and classifications concerning data revisions, see Tomczyk [2013].

As far as I am aware, the extent of data revisions in Poland and their impact on predictive properties of time series have been addressed in a single paper only [see Syczewska 2013]. General literature pertaining to data revisions and their influence on quality of forecasts or properties of expectations time series is also limited. There is a continuing (if somewhat slow-moving) debate on whether tests of expectations should be based on initial or revised data [see Zarnowitz 1985; Keane and Runkle 1990; Croushore and Stark 2001, Mehra 2002]. Recent econometric analyses on impact of data revisions on forecast quality include Croushore [2011, 2012] and Arnold [2013]. There remain many open questions concerning appropriate data vintage for scaling qualitative survey data, measuring accuracy of expectations with respect to observed values, or testing properties of expectations time series.

In my previous papers [Tomczyk 2013, 2014], review of literature and databases related to economic data revisions, reasons for introducing adjustments to already published economic data, taxonomy of revisions, and comparison of quantification results for initial and revised data on production volume index in Poland are presented. In this paper, I continue this line of research by updating results on quantification procedures and testing properties of expectations obtained for two distinctive data vintages: end-of-sample (EoS) and real time (RTV).

DESCRIPTION OF DATA[1]

Analyses of industrial production are typically based on volume index of production sold in manufacturing provided by the Central Statistical Office (CSO). In Poland, systematic data revisions in the past two decades were due to changes in the base period for the index in 2004, 2009 and 2013. In January 2013, value of reference has been set as the average monthly industrial production of 2010. To extend the sample, observations dating back to January 2005 were recalculated to be consistent with the 2010 base.

To evaluate properties of expectations collected through qualitative business tendency surveys, quantification of survey data is necessary. In this paper, longer data series is used than in an earlier paper [Tomczyk 2014], and an additional issue is addressed: that not only dependent variables in quantification models (that is, CSO data on volume index of industrial production) are subject to revisions, but so are explanatory variables (that is, qualitative data on expectations and assessments of changes in economic variables).

Expectations and subjective assessments of changes in production are collected by the Research Institute for Economic Development (RIED, Warsaw School of Economics) through monthly business tendency surveys. The survey comprises eight questions designed to evaluate both current situation (as compared to last month) and expectations for the next 3 – 4 months by assigning them to one

[1] I would like to thank Mr Konrad Walczyk, PhD (Research Institute for Economic Development, Warsaw School of Economics) for his assistance with compiling the dataset.

of three categories: increase / improvement, no change, or decrease / decline. Previous studies based on RIED survey data show that expectations series defined for three- and four-month horizons exhibit only minor differences, with a slight superiority of the three-month forecast horizon.

Let us define the following:

A_t^1 – percentage of respondents who observed increase between t – 1 and t,
A_t^2 – percentage of respondents who observed no change between t – 1 and t,
A_t^3 – percentage of respondents who observed decrease between t – 1 and t,
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 statistics 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, of 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]). In section 3, two versions of regression method are used to compare real time and end-of-sample data vintages.

RIED business survey data is also subject to revisions. Prior to 2012 revisions were sporadic: just a single one in 2010 (in April) and another in 2011 (in October). From 2012 on, adjustments become frequent. In 35 months between January 2012 and November 2014, balance statistics for assessments of changes in production has been revised a total of 19 times. In twelve cases, corrections were positive (that is, final number was larger than initial estimate by, on average, 0.64 of a percentage point). In seven cases, final number was smaller than initial estimate by, on average, 0.51 of a percentage point.

Let us employ the following notation: end-of-sample values will be marked with superscript EoS (for example, $A_t^{1\text{-}EoS}$), and real time values – with superscript RTV (for example, $A_t^{1\text{-}RTV}$). In the next section, both real time and end-of-sample data is used in regression quantification models.

QUANTIFICATION MODELS

Quantification procedures involve scaling qualitative survey data in a manner consistent with observed quantitative values, usually provided by government agencies – that is, widely available and officially endorsed data. In my earlier paper [Tomczyk 2013] I suggested that for quantification purposes, survey data should be compared with final (EoS) data rather than values available in real time because respondents are probably aiming to describe their final assessments and predictions rather than initial estimates subject to revisions. Initial attempt to test this proposition [Tomczyk 2014] has shown that end-of-sample data does indeed appear better suited to quantification of RIED business tendency survey data on volume index of industrial production. However, this conclusion was of limited reliability as none of the quantification models exhibited statistically satisfactory estimation results.

In this paper, I employ two versions of the regression method, introduced by O. Anderson [1952] and D. G. Thomas [1995], respectively. In Anderson's model, the following equation is estimated:

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

where $_{t-1}y_t$ describes relative change in value of variable y published by a statistical agency between t – 1 and t, and ν_t is a white noise error term. Parameters α and β are then estimated by OLS, and on the assumption that the same relationship holds for expectations reported in surveys, quantitative measure of expectations is constructed on the basis of the following equation:

$$_{t-1}\hat{y}_t = \hat{\alpha} \cdot P_t^1 + \hat{\beta} \cdot P_t^3\,, \tag{2}$$

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

In 1995, D. G. Thomas offered a modification of the basic Anderson model to account for the special case in which normal or typical situation that respondents compare their current circumstances to is subject to a growth rate, making observing (or predicting) decreases in dependent variable more essential than increases:

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

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

$$_{t-1}\hat{y}_t = \hat{\gamma} + \hat{\delta} \cdot P_t^3\,, \tag{4}$$

where $\hat{\gamma}$ and $\hat{\delta}$ are OLS estimates obtained on the basis of (3).

For the purpose of comparing data vintages, dependent and explanatory variables in quantification models (1) and (3) may be based on either RTV or EoS data.

In case of real time data, dependent variable in regression quantification models (that is, changes in volume of industrial production) is typically defined on the basis of volume index of industrial production sold available in real time, IP_t^{RTV}. It seems likely that respondents evaluate current changes in production against recent averages, and one quarter appears a plausible observation horizon.

Let us define

$$P_t^{RTV-AV} = \frac{IP_t^{RTV}}{\frac{1}{3}\sum_{s=1}^{3} IP_{t-s}^{RTV}} - 1 \quad (5)$$

for real time data and

$$P_t^{EoS-AV} = \frac{IP_t^{EoS}}{\frac{1}{3}\sum_{s=1}^{3} IP_{t-s}^{EoS}} - 1 \quad (6)$$

for end-of-sample data. Formulas (5) and (6) reflect changes in volume of industrial production sold as compared to the average calculated on the basis of last three months, for real time and end-of-sample data.

All quantification models are estimated by OLS with HAC standard errors – that is, Newey-West heteroskedasticity and serial correlation consistent estimators – to account for possible serial correlation and unstable variance of the error term (due to inertia in processes describing behaviour of macroeconomic variables and probable learning patterns imbedded in expectations formation processes). All models are estimated on sample from April 2005 till November 2014 (n = 116). Estimated equations take the following form:

Anderson's model for real time data: $\hat{P}_t^{RTV-AV} = 0.2883 \cdot A_t^1 - 0.2473 \cdot A_t^3$

Anderson's model for end-of-sample data: $\hat{P}_t^{EoS-AV} = 0.2866 \cdot A_t^1 - 0.2458 \cdot A_t^3$

Thomas' model for real time data: $\hat{P}_t^{RTV-AV} = 0.1241 - 0.4332 \cdot A_t^3$

Thomas' model for end-of-sample data: $\hat{P}_t^{EoS-AV} = 0.1233 - 0.4304 \cdot A_t^3$

For both data vintages and both quantification models, all estimated parameters exhibit correct signs and are different from zero at 0.01 significance level. RESET test allows to accept functional form of all quantification models as adequate, and coefficients of determination of the models are acceptable. To find basis for selecting either Anderson's or Thomas' models for further analysis, let us note that correlation coefficients between explanatory variables in Anderson's equations, both based on RTV and EoS data, are equal to approximately − 0.87. High degree of multicollinearity in Anderson's models allow to select Thomas' equations as more reliable.

Estimation results do not confirm the preliminary hypothesis that final (EoS) datasets are better suited to modeling assessments of survey respondents. Models estimated for two data vintages are very similar, both from statistical point of view and taking into account their economic interpretation.

To summarize, comparison of regression quantification models across data vintages does not provide immediate recommendations as to whether RTV or EoS data should be used in quantification procedures. In section 4, analysis is continued with expectations series constructed on the basis of the two data vintages.

TESTS OF PROPERTIES OF EXPECTATIONS

In this section, unbiasedness and weak-form orthogonality of expectations are tested. These properties are typically verified within the framework of Rational Expectations Hypothesis, and have been previously analyzed for Polish business survey respondents [see Tomczyk 2011 for review of literature]. Nonetheless, tests of rationality of expectations in Poland have failed to provide conclusive results. Whether expectations on production, prices, employment and general business conditions can be considered rational or not depends on various factors, including sample size, frequency of available data, empirical methods employed, and type of variables included in the analysis. No consistent results on rationality (or, more precisely, its fundamental components: unbiasedness and orthogonality of expectations errors to widely available information) emerge from the literature. Nardo [2003] gives one likely reason for this impasse: "The presence of measurement error in the quantified data is certainly reflected in the general disappointing performance of the standard tests of rationality in the applied literature." (p. 658) In this section, another possible reason related to data quality in addressed, that is, the issue of selecting appropriate data vintage for empirical analysis of expectations time series.

On the basis of Thomas' quantification model, expectation series for both data vintages have been constructed. It is assumed that one-month observed changes and three-month expected changes in production are described by the same regression parameters. This simplification constitutes a substantial weakness of regression method, shared by all commonly used quantification methods. It cannot be tested, however, on the basis of dataset available from the RIED business tendency survey as detailed data on individual survey respondents would be required for this purpose.

Two expectations time series have been constructed, that is:

$$E_t^{RTV} = 0.124058 - 0.433176 \cdot P_t^{3-RTV} \tag{7}$$

for real time data and

$$E_t^{EoS} = 0.123343 - 0.430448 \cdot P_t^{3-EoS} \tag{8}$$

for end-of-sample data. To test for unbiasedness, I employ procedure based on unit root tests of expectations and corresponding observed time series [see Liu, Maddala 1992, Maddala, Kim 1998, Da Silva Lopes 1998] which has been extensively used in empirical tests of rationality of expectations. Results of the Augmented Dickey-Fuller test of nonstationarity of expectations series (E_t^{RTV}, E_t^{EoS}) and observed changes in industrial production ($P_t^{RTV\text{-}AV}$, $P_t^{EoS\text{-}AV}$) are presented in

Table 1. All test equations have been estimated with a constant and maximum lag set to 12 on the basis of the modified AIC criterion.

Table 1. Results (p-values) of ADF test for expectations and observed production series

		Levels	First differences	Degree of integration
Expectations series	E_t^{RTV}	0.5581	0.0000	I(1)
Observed variable	P_t^{RTV-AV}	0.4237	0.0000	I(1)
Expectations series	E_t^{EoS}	0.3494	0.0000	I(1)
Observed variable	P_t^{EoS-AV}	0.4298	0.0000	I(1)

Source: own calculations

It is clear from Table 1 that all series are integrated of order one. Preliminary condition for expectations series being unbiased predictors of observed series is therefore met, and subsequent conditions may be tested: whether expectations and realized changes in production are cointegrated, and whether the cointegrating parameter is equal to 1 [see Da Silva Lopes 1998]. The following equations are therefore estimated:

$$P_t^{RTV-AV} = \lambda_1 + \mu_1 \cdot E_{t-3}^{RTV} + \varepsilon_{1t} \tag{9}$$

and

$$P_t^{EoS-AV} = \lambda_2 + \mu_2 \cdot E_{t-3}^{EoS} + \varepsilon_{2t}, \tag{10}$$

in which explanatory variables have been lagged three months to account for the 3-month forecast horizon used in RIED business tendency surveys. Models have been estimated by OLS with HAC standard errors. Results of the ADF test for residuals in models for both data vintages, and of the test of linear restriction reflecting the postulated cointegrating vector, are presented in Table 2.

Table 2. Cointegrating regressions

	p-value for ADF test of residuals	p-value for restriction
Real time data	p = 0.3561	H_0: $\mu_1 = 1$ in (9) p = 0.0000
End-of-sample data	p = 0.0000	H_0: $\mu_2 = 1$ in (10) p = 0.0000

Source: own calculations

In case of real time data, null hypothesis of nonstationarity of the residuals in equation (9) cannot be rejected, that is, expectations and corresponding observed changes in production are not cointegrated. For end-of-sample data, however, null hypothesis is rejected at every typical significance level. It follows that expectations and observed changes in production are in fact cointegrated for series based on the end-of-sample data. Yet, the null hypothesis of cointegrating parameter being equal to one is rejected, and consequently neither of the data vintages lead to unbiased expectations of changes in production. To summarize: there is a notable difference between RTV and EoS data vintages: a cointegrating relation exists only for EoS data. In this case, there is a stable linear combination (that is, expectations and observed series do not diverge in the long run) but it does not support the hypothesis of unbiasedness of expectations.

Unbiasedness tests are considered to be very sensitive to measurement errors and are often supplemented with tests of orthogonality (sometimes also called informational efficiency) of expectations errors with respect to freely available information [see Pesaran 1989, Da Silva Lopes 1998]. Tests of orthogonality are classified as weak, when information set includes only lagged values of variable being forecasted, or strong, when the information set contains additional exogenous variables. I propose to test weak-form orthogonality of expectations errors with respect to production volume data lagged up to three months. I believe that this sets the upper limit on information set of business tendency survey respondents who are not professional forecasters.

The orthogonality hypothesis for RTV data may be therefore written as follows:

H_0: $\kappa_1 = \kappa_2 = \kappa_3 = 0$,

where

$$P_t^{RTV-AV} - E_{t-3}^{RTV} = \kappa_0 + \kappa_1 \cdot P_{t-1}^{RTV-AV} + \kappa_2 \cdot P_{t-2}^{RTV-AV} + \kappa_3 \cdot P_{t-3}^{RTV-AV} + \theta_{1t}, \tag{11}$$

and for end-of-sample data as

H_0: $\omega_1 = \omega_2 = \omega_3 = 0$,

where

$$P_t^{EoS-AV} - E_{t-3}^{EoS} = \varpi_0 + \varpi_1 \cdot P_{t-1}^{EoS-AV} + \varpi_2 \cdot P_{t-2}^{EoS-AV} + \varpi_3 \cdot P_{t-3}^{EoS-AV} + \theta_{2t}. \tag{12}$$

Equations (11) and (12) have been estimated by OLS with HAC standard errors. Since three lagged variables are used and therefore multicollinearity of explanatory variables may pose a problem, Variance Inflation Factors are also verified, and found to be equal to 1.18 – 1.22 and to indicate absence of serious multicollinearity. Results of orthogonality tests are presented in Table 3.

Table 3. Results of orthogonality tests

	p-value for restriction
Real time data	H_0: $\kappa_1 = \kappa_2 = \kappa_3 = 0$ in (11) $p = 0.0000$
End-of-sample data	H_0: $\omega_1 = \omega_2 = \omega_3 = 0$ in (12) $p = 0.0000$

Source: own calculations

From Table 3 it is clear that the null hypothesis of insignificance of explanatory variables is rejected. Expectation errors are therefore not orthogonal to easily available information on changes in production index. It follows that RIED business tendency survey respondents do not efficiently make use of available data; specifically, second and third lags of explanatory variables $P_t^{RTV\text{-}AV}$ and $P_t^{EoS\text{-}AV}$ are statistically significant. It seems that when forming their expectations pertaining to volume of industrial production, business tendency survey respondents do not take data older that one month into account.

CONCLUSIONS AND DIRECTIONS FOR FURTHER RESEARCH

In this paper, results of quantification procedures and properties of expectations series obtained for two data vintages are described. Empirical analysis confirms that while there are only minor differences in quantification results with respect to data vintage, properties of expectations time series obtained on their basis do diverge. Specifically, there exists a cointegrating regression for one of the vintages only, that is, end-of-sample data. In this case, expectations and observed changes in industrial production exhibit similar long-run properties. Neither of the expectations series, however, constitutes prediction of changes in production that is unbiased or employs available information efficiently.

The research project on impact of data vintage on properties of expectations is continued with the following points considered for further analysis:

- use of other business tendency survey series to scale Central Statistical Office data,
- extending the test of orthogonality to include additional variables in the information set of survey respondents,
- describing and evaluating extent of data revisions in Research Institute for Economic Development business tendency survey data.

Empirical studies of impact of data revisions on expectations promise to assist economists in drawing more general conclusions on behavior and properties of expectations series, including predictive quality, unbiasedness and efficient use of available information. Based on analysis presented in this paper, data vintage does matter in determining basic properties of expectations time series.

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