

Emilia Tomczyk<sup>±</sup>

## **End-of-sample vs. Real-time Data: Perspectives for Analysis of Expectations**

### **Abstract**

Data revision is usually defined as an adjustment published after initial value had been announced; it may reflect rectification of errors, availability of new information, introduction of new measurement or aggregation techniques etc. This paper addresses the impact of data revisions on measures of expectations and offers an introduction to empirical analysis of data vintage in testing properties of expectations. It also defines and classifies data revisions and presents a review of literature and databases available for the purposes of real time analysis.

Keywords: end-of-sample (EOS) data, real-time (RTV) data, data revisions, economic databases, expectations

JEL classification: C82, D84

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<sup>±</sup> Institute of Econometrics, Warsaw School of Economics

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## 1. Introduction

Data revision can be generally described as an adjustment published after the original announcement had been made; it may reflect rectification of errors, availability of new information, introduction of new measurement or aggregation techniques, etc. Data revisions may be planned or unexpected, regular or occasional, major or of little significance. Only recently it has been acknowledged in literature that while economic agents have access to real-time data only, econometricians who analyse their behaviour usually employ end-of-sample databases. Whether this discrepancy influences results of economic analyses, and what are the pros and cons of using real time vs. end-of-sample datasets, has newly evolved into a separate branch of empirical econometrics literature, reviewed in section 3.

Historically, econometricians tended to ignore the issue of data revisions. Most analyses were based on final values accessible at the moment of model estimation, and real-time data were not easily available. (Situation has since somewhat improved, at least in the US and OECD countries; see section 4.) Croushore & Evans point out that ‘since government agencies and private sources do not provide these data conveniently, these shortcuts are rarely questioned’ (2006, p. 1159). They are questioned in post-2006 literature, however, and open a new field of research for applied economists.

This paper presents a review of literature and databases available for the purposes of real-time analysis, and offers an introduction to empirical analysis of influence of data vintage on tests of expectations. Several formal methods of analyzing expectations are available, among them descriptive statistics, *ex post* forecast errors, tests based on frequency tables, entropy measures, and tests of properties of expectations time series. The latter typically consist of testing properties associated with Muth rationality: unbiasedness and orthogonality with respect to available information. To supplement and improve testing procedures, I propose to address the issue of data revisions. Revised values may significantly differ from original values, and there may be several steps between initial and final – that is, unchanged in any later publications – data. Database users may not even be aware that some of the values have been modified, perhaps repeatedly, and corrected numbers may significantly differ from original ones. It should perhaps be obvious that ‘an economist *ex post* can use several-times revised macroeconomic data, while an investor in real time can only use preliminary first releases of macroeconomic data’ (Hartmann 2007, p. 7). Let us substitute ‘economic agent’ or ‘decision maker’ for ‘investor’, and the magnitude of the data vintage problem becomes evident.

Questions that arise in relation to data revisions concern the crucial issues of expectations analysis. For example, should initial or final data be used to compare expectations with their realizations observed at a later date? To quantify survey expectations data? To evaluate unbiasedness and orthogonality of expectations time series? Data vintage is likely to influence results of quantification procedures and tests of properties of aggregated expectations time series.

## 2. Definitions

End-of-sample (EoS) data is usually defined, following Koenig *et al.* (2003), as data from the latest available announcement – that is, from researcher’s point of view, final data. It is important to keep in mind that by the time researcher uses a database, some or even most of the variables had been revised many times, reflecting corrections of errors, newly available information, introduction of new measurement or aggregation techniques, updating the base period for real variables, etc. On the other hand, real-time values (RTV) are initial values, made available by statistical agency (or other publisher) directly after their collection; they are ‘snapshots’ taken at a particular moment in time.

To help describe what data is actually available to economic agents when they make their decisions (or express expectations, or declare observed changes in economic variables), the term ‘vintage’ is used. Following Swanson (1996), most researchers (for example, Croushore & Stark, 2002; Kozicki, 2004; Hartmann, 2007) define ‘vintage’ as a data set corresponding to the information available at a particular date, and ‘real-time dataset’ as collection of vintages.

To complicate matters, the term ‘final data’ is far from clear. When end-of-sample values (latest available, as defined above) become truly final? In fact, EoS data are likely to present a combination of initial, partly revised, and final data. To distinguish between final and partly revised data, Stark & Croushore (2002) propose the following interpretations of ‘final’: the latest value available; last value before a benchmark revision; value available one year after the observation date. In a later paper Croushore (2006a) introduces the term ‘actuals’ to denote partly revised real-time values. However, it is evident that none of these definitions guarantees ‘final’ values in the common sense of the word, and does not help in selecting between alternative concepts of actuals in a particular empirical study, or evaluate the extent of consequent data revisions.

Christoffersen *et al.* (2002, p. 346) identify the following categories:

- preliminary or first released or unrevised data: first reported value for each variable at each calendar date;

- partially-revised real-time data: vectors of observations for each variable at each calendar date (data vintages);
- fully revised or final data: revised figures that are no longer subject to any revision in the future.

However, researcher cannot be sure that the variables he or she is using will never again be revised; in theory, the revision process can be infinite. Definition of ‘end-of-sample’ data must be therefore specified for every empirical analysis, and addressed in context of datasets available.

Several classifications of data revisions are available. Croushore & Stark (2002) discuss information-based data revisions (when additional information becomes available to correct initial estimates) and structural data revisions (due to changes in the system of national accounts, aggregation methods, base years for real variables, changes in definitions etc.) Other categorizations found in literature distinguish data revisions that are either planned or unplanned, and either regular or occasional.

Generally, published data may be, for lack of a better word, ‘final’ (that is, not expected to change) or provisional (that is, subject to planned revision). Typical reasons for planned revisions reflect availability of information that regularly arrives too late for initial announcements or introduction of seasonal adjustments calculated on the basis of data unavailable at the time of the original announcement. Unplanned data revisions may result from various errors, unplanned modifications of methodology or statistical classifications, unpredictable difficulties in data collection and processing, etc. All unplanned data revisions are occasional; regular adjustments typically include seasonal and other calendar effects.

Another classification addresses purpose of data revisions. Modifications introduced by statistical agencies are meant to reflect the arrival of new information which became available only after the initial announcement has been made, or correct errors that had been made earlier. Specifically, McKenzie (2006, p. 7) lists the following reasons for revisions of official statistics:

- incorporation of data with more complete or otherwise better reporting (eg including late respondents or additional data sources) in subsequent estimates.
- correction of errors in source data and computations.
- replacement of first estimates derived from incomplete samples when more accurate data become available.
- incorporation of source data that more closely match the concepts and/or benchmarking.
- incorporation of updated seasonal factors.
- updating of the base period of constant price estimates.

- changes in statistical methodology, concepts, definitions, and classifications.

Jacobs & van Norden (2010, p. 1) add one more reason to the above list: revisions to national accounts statistics based on analysis of supply and demand (input-output) tables.

Points 5 to 7 on McKenzie's list draw attention to the fact that revisions can also result from reasons external to economic content of variables, such as change of the definition of a variable, or weighting procedures used in its construction, or similar issues. Revisions of this type, pertaining to definitions or statistical procedures and not the economic data themselves, are sometimes called spurious revisions. Usually, efforts are made by statistical agencies to remove effects of spurious revisions from the published data, and make the newly published data set compatible with previous values. Both extent and efficiency of these efforts are, however, difficult to determine.

The question of EoS vs. RTV data can be examined in the wider context of news-or-noise framework first introduced by Mankiw *et al.* (1984) and Mankiw & Shapiro (1986). They describe 'noise' as opposed to 'news' and define the latter as efficient messages, incorporating all available and relevant information. For the practical purposes of distinguishing between 'news' and 'noise' components, Croushore & Stark offer the following description: 'if the revisions are characterized as containing news, subsequent releases of the data for that date contain new information that was not available in the earlier releases. [...] This implies that the revision to the data is correlated with the revised data but not with the earlier data. [...] On the other hand, if data are characterized as reducing noise, subsequent releases of the data just eliminate noise in the earlier release [...]. In this case, the revision should be uncorrelated with the revised data, but correlated with the advance data' (2002, p. 9-10). The news and noise components are subject to testing. For example, Mankiw *et al.* (1984) test whether preliminary announcements of money stock are better described by news hypothesis (that is, initial data are rational forecasts of the final values, and revisions are caused only by new data becoming available) or noise hypothesis (that is, initial announcements are observations of final, or revised values but are measured with an error). This strand of research is continued in recent literature (see for example Borağan Arouba, 2008, and McKenzie *et al.*, 2008).

Jacobs and van Norden (2010) classify data revisions into an even wider field of measurement errors. In addition to 'noise' component (which they define in terms of uncorrelated measurement errors from different data vintages) and 'news' component (defined as characterized by measurement errors equal to rational forecast errors), they propose to consider a 'spillover'

component in which measurement errors within a given data vintage are serially correlated.

Typically researchers make every effort to include final (revised) values – that is, EoS data – in their analyses of economic variables, hoping to find them free from initial errors. Only recently the consequences and benefits of employing RTV data has been addressed and analysed. The following reasons may be given for the attention this subject has commanded:

1. As mentioned above, only initial data are available in real time to decision makers, and consequently ‘economist who uses revised macroeconomic data implicitly makes unrealistic assumptions about the timeliness of data availability’ (Hartmann, 2007, p. 2). Ignoring the characteristics of information set available to economic agents may lead to incorrect conclusions concerning, for example, quality of their forecasts.
2. Real-time economic data enables researchers to reproduce each others' research, even in case of projects based on old and since updated data.
3. Real-time datasets make it possible to evaluate policy decisions using data available at the time.

To illustrate the significance of data vintage selection for results of econometric analysis, Croushore & Stark (2002) examine several influential papers by F. E. Kydland & E. C. Prescott, R. E. Hall & O. J. Blanchard and D. Quah. They focus on impact of data revisions on major macroeconomic studies, and comment on robustness of these studies to changes in the data set. They obtain mixed results; while some of the analyses are confirmed with real time data, and are qualitatively robust for different data vintages, others do not ‘stand the test of time, either in terms of revisions to the data or in terms of additional data’ (p. 17) and prove to be sensitive to the selection of data vintage. Croushore & Stark’s work clearly shows that the issue of data vintage and its significance for results of empirical econometric studies deserves more attention.

### **3. Review of literature**

Data revisions have been analysed extensively, if only recently. Even though Jacobs & van Norden (2010) look back to 1919, when Persons’ paper was published in *The Review of Economics and Statistics*, they identify the launch of real-time data analysis with comparative analyses of GDP from the 1950s and 1960s. Publication usually credited with launching this branch of economic research is the 1955 article by Gartaganis & Goldberger published in *Econometrica* (see Croushore, 2011). Soon, Zellner (1958) compared

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provisional estimates of quarterly GNP components with their currently available (revised and presumably final) values. As early as 1950, Morgenstern (1963) pointed out importance of measurement errors in economic data. Classified and described by Pierce (1981), and modeled with errors in variables by Klepper and Leamer (1984) and Griliches (1986), measurement errors created an extensive framework for description and study of data revisions.

Since then, the field has expanded and produced numerous research papers on comparisons of forecasts built on the basis of real-time (initial) data and the latest available (final) data, macroeconomic research (including fiscal and monetary policy), influence of macroeconomic data revisions on financial markets, and current analysis of business and financial conditions. Various authors reviewed this literature from different points of view (see Croushore 2006b, 2011; Hartmann, 2007; Borağan Aruoba, 2008; Clements & Galvão, 2010; Cimadomo, 2011) and offered a variety of classifications of the major themes within this field. In this section, I make an attempt to summarise major topics and organise them into the following sections: studies of predictability and significance of data revisions; studies of frequency and regularity of data revisions; analyses of impact of data revisions for macroeconomic forecasting; importance of data vintage in policy making and, finally, in empirical finance.

### 3.1. Predictability and significance

This line of literature addresses the following question: how large and how systematic are data revisions in key macroeconomic variables? If revisions to the data are small and unpredictable, the use of any data vintage would lead to qualitatively similar results; if there are large or systematic, conclusions drawn from empirical studies may be influenced by data vintage. Beginning from the 1980s, publications focus on variables such as money stock and GDP (see Mankiw *et al.*, 1984; Mankiw & Shapiro, 1986; Mork, 1987). The majority of authors find revisions both large and predictable but there is some disagreement on whether they have a significant effect on estimated monetary policy rules. Croushore (2006b, 2011) presents evidence that some data revisions, even after discounting seasonal adjustments, are systematic and predictable and may be a factor in expectations analysis. These findings suggest that institutions which publish and revise economic data can introduce adjustments in the original (preliminary) values in expectations of future revisions, in order to minimise the extent of subsequent updates. However, while revisions in some variables are systematic and predictable, they are unpredictable or very small in others; generally, Croushore shows that revisions do influence quality of forecasts. Borağan Aruoba (2008) confirms these results; he finds initial announcements made by statistical agencies biased, and

revisions – large compared to initial data. He concludes that revisions are predictable with information available at the time of the initial announcement. Cimadomo (2011) shows that fiscal data revisions are large, biased and predictable, and that different fiscal policies are suggested by use of real time data as compared to use of end-of-sample data.

A summary of previous research on this subject is presented in Arnold (2012); on the basis of earlier publications and her own research, she concludes that whether announcements are revised systematically, and whether economic agents aim at forecasting final or initial values, influences evaluations of forecast accuracy, and finds revisions considerable and at least partly predictable.

Empirical analysis has been centered on, but not limited to, United States. Faust *et al.* (2005) confirm predictability of revisions in GDP growth rates in G-7 countries; in several cases they find updates large and predictable. Golinelli & Parigi (2007) evaluate forecasting performance of preliminary releases of GDP growth for various vintages of US and Italian data. To summarise, data revisions are generally found to be large and, at least to some extent, predictable – although whether they are significant for policy making purposes remains to be seen.

### 3.2. Frequency and regularity

This strand of literature addresses the crucial question of data revisions: when a value can be considered final? Following section 2, revisions may be classified as occasional (for example, benchmark revisions) or regular (for example, with frequency compatible with publication cycle or seasonality patterns). Jacobs & van Norden (2010) propose a framework to distinguish regular revisions from ‘surprise’ ones, and first revisions from subsequent updates. They conclude that measurement errors introduced by data revisions are characterised by complex dynamics which were not included in previous models, and propose methods to differentiate between ‘first’ and ‘later’ revisions. As far as benchmark revisions are concerned, Kozicki (2004) finds them important for monetary policy purposes, and Phillips & Nordlund (2012) show that there is a cyclical and seasonal bias in the annual benchmark revisions in employment data. In general, both regular and irregular revisions seem to influence results of econometric modeling, and including revisions in a research procedure is far from straightforward.

Recently, Franses (2013) finds that data revisions introduce periodic properties (that is, seasonal heteroscedasticity and serial correlation patterns) into economic data. On the basis of quarterly macroeconomic time series he concludes that seasonal characteristics of data change with data vintage. This



finding confirms that seasonal adjustments should be based on thorough knowledge of seasonality patterns, and that procedures used to eliminate consequences of heteroscedasticity and serial correlation on properties of estimators should take into account regular data revisions.

### 3.3. Macroeconomic forecasting

This strand of literature focuses on effects of data vintage on specification of econometric models and evaluation of forecast errors. Two important issues arise within this framework:

- which data vintage is included in the information set of forecasters, and whether forecasts made by economic agents are sensitive to the data vintage;
- which data vintage should be used to evaluate forecasts.

Historically, the second question has gained more recognition. One of the most active researchers in the field of data revisions, D. Croushore, writes: 'Before we examine the quality of the forecasts, we must tackle the difficult issue of what to use as actuals for calculating forecast errors. [...] But forecasters are quite unlikely to have anticipated the extent of data revisions to the price index that would not occur for many years in the future. More likely, they made their forecasts anticipating the same methods of data construction being used contemporaneously by the government statistical agencies' (2006a, p. 8).

One of the first papers that helped to draw attention of economic community to issues of data vintage in forecasting is Zarnowitz & Braun's (1992) comprehensive review of quarterly survey of professional macroeconomic forecasters. They examine various forecast evaluation techniques, some of them based on initial values, others – on revised data. They find that forecast errors tend to increase with size of revisions, but there are exceptions to this rule, and choice of data vintage does not seem to be a critical factor in forecast evaluation. They also stress that a single data vintage is unlikely to become a general standard for forecast evaluation, and any choice made in a particular case will be arbitrary.

Since then, many researchers attempted to assess whether use of EoS data causes overestimation of predictive value of explanatory variables, or influences forecasts quality, as compared with use of RTV values (keeping in mind that only RTV data were available when forecasts were initially formed). While many papers addressing these issues were published (see Diebold & Rudebusch, 1991; Swanson, 1996; Orphanides, 2001; Croushore & Stark, 2001, 2003; Faust *et al.*, 2003; Orphanides & van Norden, 2002; Stark & Croushore, 2002; Clements & Galvão, 2010; Croushore, 2012), evidence remains mixed.

For example, Diebold & Rudebusch find more predictive power in revised than in real-time data, but majority, most forcefully Swanson and Clements & Galvão find advantages of real-time data as compared to end-of-sample values in terms of minimising the expected squared forecast error. Croushore (2012) examines four different definitions of output and inflation, and finds that results of tests of forecast bias heavily depend on data vintage. Koenig *et al.* (2003) discuss efficiency of including different vintages of data; they conclude that use of real time data can overestimate the forecasting power of a model relative to alternative models.

Croushore (2006b) presents a review of literature on data revisions and optimal forecasts, and summarises results of his own research. He offers the following general findings:

- forecasts based on EoS and RTV data differ, and predictive content of variables may change as the result of data revisions;
- forecasts of level variables are revised more often than forecasts of growth rates;
- model choice is influenced by data revisions;
- number of lags in ARIMA-class models is influenced by choice of data vintage.

Influence of data vintage on macroeconomic forecasting seems therefore to be substantial.

A related issue concerns proper response to data revisions when forecasting in real time. It is unclear whether using multiple data vintages improves accuracy of forecasts; Croushore (2006b) does not find improvement in including (as opposed to ignoring) data revisions; Clements & Galvão (2010), using VAR methodology, do find advantages of RTV over EoS data, and in a later publication (2011) show that historical (RTV) data supplements EoS values for the purpose of real-time policy analysis. The authors see their results as the supportive for employment of multiple-vintage models.

Structural approach has also been used for the purpose of multi-vintage analysis of forecasting models. For example, Vázquez *et al.* (2012) propose an extended version of the basic New Keynesian model which includes revision processes of output and inflation data in order to assess the importance of data revisions on monetary policy and on transmission of policy shocks. They find that even though the initial announcements of output and inflation are not rational forecasts of revised data, 'ignoring the presence of non well-behaved revision processes may not be a serious drawback in the analysis of monetary policy in this framework' (p. 29).

A separate strand of literature groups technical papers on forecasting revised data in real time using the Kalman filter (see Conrad & Corrado, 1979)

and, later on, more advanced methods, among them non-linear and non-Gaussian filters (see Mariano & Tanizaki, 1995). Related papers address the topic of data vintage in presence of measurement errors (see Harrison *et al.*, 2005; Jacobs & van Norden, 2010) and modeling multivariate data revisions in systems of variables with linear state space models (see Patterson, 2003; Croushore, 2006b; Jacobs *et al.*, 2010). State-space models are often used for the purpose of vintage data analysis; when revision process is presented in state-space form, standard filtering techniques can be used for estimation, inference, forecasting and imputation of missing data. Perhaps the most comprehensive description was provided by Jacobs & van Norden (2010). They place updated series within measurement error models and propose a space-state framework designed to model a wide set of measurement errors, including data revisions.

### 3.4. Policy making

There are numerous papers on influence of data revisions on monetary policy; for example, Orphanides (2001) shows that policy measures based on initial data – that is, values available at the time policy decisions were made – would be different if undertaken on the basis of revised data. Use of real-time data in analyses of fiscal policy has also been extensively studied (see Forni & Momigliano, 2005; Golinelli & Momigliano, 2006; Bernoth *et al.*, 2008; Cimadomo, 2008; and Beetsma *et al.*, 2009, published under the enticing title ‘Planning to cheat: EU fiscal policy in real time’). The vast literature has been reviewed in Cimadomo (2011), and its major findings were summarised as follows: revisions in fiscal data tend to be large and systematic; strong fiscal rules promote accurate reporting and smaller revisions; and ‘the ex-ante reaction of fiscal policies to the economic cycle is estimated to be more “counter-cyclical” when real-time data are used instead of ex-post data’ (p. 30). To summarise, monetary and fiscal policy decisions are sensitive to vintage of data used for their evaluation.

What is more, importance of data revisions depends on the type of VAR model used; some VAR systems employed for monetary policy analysis may not even be identified when vintage of data is adjusted. Croushore & Evans (2006) show that ‘the use of revised data in VAR analyses of monetary policy shocks may not be a serious limitation for recursively identified systems, but presents challenges for simultaneous systems’ (p. 1135). Therefore, data vintage may not only influence evaluation of policy decisions, but, more significantly, introduce a qualitative change into methodology of analysis.

### 3.5. Empirical finance

Empirical finance literature includes a number of analyses on usefulness of macroeconomic data in predicting stock market returns, following the lead of E. F. Fama in the 1970s. While predictive power of macroeconomic volatility for stock markets volatility is generally confirmed, data revisions in macroeconomic variables, and their influence on financial markets, are usually overlooked.

The last decade brought several papers on effects of data vintage for financial analysis. Christoffersen *et al.* (2002) study implications of real-time data use for sensitivity of asset prices to economic news. They find that evaluation of dependence of financial returns on macroeconomic data changes with data vintage, and may supply misleading results when data availability and timing issues are ignored. They particularly stress that importance of measuring impact of macroeconomic news on the fact that revisions tend to accumulate over time and may be significant, and substantial, in aggregate.

On the other hand, several researchers find that influence of data vintage on financial markets analyses is small or insignificant, or mixed. Hartmann (2007) analyses 'whether using real-time macroeconomic data instead of revised macroeconomic data has any implications on the results for empirical finance' (p. 2). On the basis of quarterly data for US, UK and Germany, he finds that using real-time instead of revised data does not significantly influence out-of-sample predictability of stock returns or of the stock market volatility. Also, performance of investment strategies is similar, and even when differences between data vintages are substantial and unpredictable, and systematic patterns of revisions are observed, they do not significantly influence investment performance. The only special case in which results are sensitive to data vintage are tests of consistency with a highly structured asset pricing model.

Döpke *et al.* (2006) also find that effects of data vintage on analyses of stock market returns are small and not significant. They show that using real-time data does not improve *ex ante* predictability of stock market returns, and whether investors have access to initial or revised macroeconomic data does not significantly influence performance of their investment portfolios.

To summarise, evidence of sensitivity of empirical financial analyses to revisions of macroeconomic data remains unclear and calls for further study.

## 4. Sources of information on data revisions

Until recently, analysis of data revisions required painstaking work on matching values published in tens (or hundreds) of paper publications over

many points in time. In the past two decades, databases containing both real-time data and subsequently revised time series became available in the US and European countries. Accessibility of these data sets makes it possible to assess the extent of data revisions.

The most comprehensive real-time database is the OECD data set which in addition to all OECD countries also includes the Euro zone countries, China, India, Brazil, South Africa and the Russian Federation. The Web interface<sup>1</sup> allows access to data for 21 economic variables as originally published in each monthly edition of the Main Economic Indicators database from February 1999 as well as the revisions made to initially published data. The key economic variables include Gross Domestic Product and its expenditure components, industrial production, production in construction, balance of payments, composite leading indicators, consumer prices, retail trade, unemployment rates, civilian employment, hourly earnings, monetary aggregates and international trade values. Time series dating back to the 1960s are provided for some variables.

The declared purpose of the database is to provide originally published data for researchers interested in testing performance (for example, forecasting performance) of econometric models in simulated real-time and to provide data for studies of influence of data revisions, for example analyses of magnitude and direction of revisions to published statistics.

Another database, widely used in applied research, is the Federal Reserve Bank of Philadelphia Real-Time Data Set (RTDS)<sup>2</sup>. Introduced in Croushore & Stark (2001) and credited with generating current interest in the analysis of influence of data vintage in economics, it is extensively employed for macroeconomic analysis of effects of data revisions and for analysis based on real-time data (see Croushore & Stark, 2003; Croushore, 2006b). It provides the information set that would be available to a forecaster on a 15<sup>th</sup> day of the middle month in every quarter, starting in 1965 and covering quarterly data on, among other variables, real and nominal output, consumption, investment and price and employment series. Its limitation is that it covers US data only.

Another branch of the Fed system, Federal Reserve Bank of St. Louis, also publishes vintage data. Its ALFRED database<sup>3</sup> (Archival Federal Reserve Economic Data, also known as Economic Data Time Travel) provides vintage versions of economic data that were available on specific dates in history. The database currently covers 65,037 series in 9 categories, with the earliest vintage

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<sup>1</sup> Database available at <http://stats.oecd.org/mei/default.asp?rev=1>.

<sup>2</sup> Database available at <http://www.phil.frb.org/econ/forecast/reaindex.html>.

<sup>3</sup> Database available at <http://alfred.stlouisfed.org/>

for the Industrial Production Index being 1927. This data set is also limited to US series.

Vintage data for European economies is published by The Euro Area Business Cycle Network (EABCN). This organisation seeks to provide an interface for policy makers from central banks and other central institutions, including the European Central Bank and academic researchers. Its Real Time Database<sup>4</sup> (RTDB) covers data for the Euro area and other European countries, and includes over 200 macroeconomic time series of different vintages, acquired from ECB's Monthly Bulletin reports.

Less comprehensive sources are sometimes used, for example vintage data on labor productivity published by the Bureau of Labor Statistics (see Borağan Arouba, 2008). Generally, there seem to be abundant sources of economic real time data, however, the most complete of them are limited to United States series.

## 5. Data revisions in Poland

To the best of my knowledge, there is no Polish database dedicated to collecting real-time economic data. Poland is included, however, in the OECD data set described in the previous section. Searching this database demonstrates that some of the data remain virtually unchanged in subsequent publications. For example, from September 2010 till May 2011, data on civilian employment in Poland for the period of third quarter of 2002 – fourth quarter of 2010 have not changed<sup>5</sup>. Similarly, in the same period data on the Consumer Price Index (measured as the average changes in the prices of consumer goods and services purchased by Polish households with 2005 level = 100) values for January 2008 – February 2011, published from September 2010 to May 2011, have not been adjusted. On the other hand, data on business conditions (namely, the composite leading indicator) exhibit modifications across the dataset. From July 2011 till April 2012, values for January 2008 – December 2011 have changed significantly in many cases.

For the variables not included in the OECD data set, it is necessary to collect historical data from individual paper or electronic publications. Publications of the Central Statistical Office (CSO) report the most recent version and if any adjustments to earlier data are introduced, the researchers have to identify them themselves. CSO occasionally publishes notes on revisions. They generally result from conforming with ESA 1995

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<sup>4</sup> Database available at <http://www.eabcn.org/>; detailed description published in Giannone *et al.* (2010).

<sup>5</sup> Database accessed in August 2012.

(The European System of Accounts, most recently updated in 1995), recommendations of Directorate-General of the European Commission (Eurostat), continuing efforts to improve quality of statistics, and new legal documents of UE (see CSO 2007). These revisions include:

- revision of national accounts for the years 1995-2004 (in 2005);
- revision of national accounts; regional accounts were re-calculated on the basis of revised data (in 2007);
- revision of public deficit and central and local government debt for the years 2005-2008; they were caused by change of methods of valuating income taxes, and including transactions relating to public-private partnerships (in 2009).

National Bank of Poland also publishes occasional announcements on data revisions. For example, on June 29<sup>th</sup>, 2011 National Bank of Poland declared continuing negative balance of errors and omissions and, in cooperation with the IMF, revised its balance of payments for years 2004-2010. Probable revisions in the Polish GDP and other macroeconomic series are discussed in financial press and internet forums. For example, on March 22<sup>nd</sup>, 2013 The Wall Street Journal has quoted the Ministry of Finance economist, Ludwik Kotecki, as saying that ‘economic expansion in Poland is likely to slow to 1.5%-2% this year, putting budget revenue under pressure and potentially forcing the government to revise its budget deficit goals’<sup>6</sup>. Nevertheless, announcements of the National Bank of Poland and the Ministry of Finance do not provide amount of data necessary for systematic analysis of data revisions and their influence on the Polish economy.

To summarise, access to initial or preliminary (and subsequently revised) Polish economic data is difficult and constitutes a challenge for empirical analysis of effects of data revisions. Any attempt to analyse Polish real-time data, and to evaluate influence of data vintage on behavior of economic time series, either must be based on data available in the OECD database or will require building a specialised data set on the basis of numerous Central Statistical Office publications. The latter option, though time-consuming, appears promising.

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<sup>6</sup> ‘Polish Budget Stressed as Growth to Slow’, by P. Wasilewski (2013), *The Wall Street Journal* (<http://blogs.wsj.com/emergingurope/tag/ludwik-kotecki/>).

Bulletins, announcements and comments published by CSO and other government agencies on data revisions concern highly aggregated data only. A closer look reveals that less aggregated data are also subject to adjustments. As pointed out in my earlier publication (Tomczyk, 2011, p. 161), the Polish index of general business conditions undergoes significant revisions; forecasts of general business conditions in November 2007 differ by 4 percentage points between March 2008 and November 2008. Such noticeable revisions offer an opportunity to test whether they influence other economic variables, and whether data vintage has a significant impact on the results of empirical analysis of Polish time series. As of 2009, there are revisions published monthly for seasonally adjusted data (see Table 1). There have been no revisions to seasonally unadjusted data since 2009. Corrections introduced in general business conditions data seem to result from an update of seasonal factors, but this procedure is not acknowledged in CSO publications, and reasons for introducing regular seasonal adjustments are not given.

Table 1. Revisions to the indicator of the general business tendency climate in manufacturing, seasonally adjusted.

|                | Real-time data (first announcement) | End-of-sample data (as of June 2012) | Size of revision |
|----------------|-------------------------------------|--------------------------------------|------------------|
| January 2011   | 1.7                                 | 1.0                                  | -0.7             |
| February 2011  | 5.1                                 | 4.1                                  | -1.0             |
| March 2011     | 4.5                                 | 3.4                                  | -1.1             |
| April 2011     | 2.1                                 | 1.7                                  | -0.4             |
| May 2011       | 2.0                                 | 1.7                                  | -0.4             |
| June 2011      | 2.1                                 | 1.6                                  | -0.5             |
| July 2011      | 2.5                                 | 1.6                                  | -0.9             |
| August 2011    | 0.1                                 | 0.0                                  | -0.1             |
| September 2011 | -1.4                                | -1.0                                 | 0.4              |
| October 2011   | -0.3                                | -0.7                                 | -0.4             |
| November 2011  | -1.4                                | -1.4                                 | 0.0              |
| December 2011  | -2.0                                | -1.7                                 | 0.3              |

Source: CSO monthly bulletins.

Similarly, there are systematic adjustments to the monthly data for the index of sold manufacturing production (see Table 2).



Table 2. Revisions to the index of industrial production in manufacturing.

|                | Real-time data (first announcement) | End-of-sample data (as of June 2012) | Size of revision |
|----------------|-------------------------------------|--------------------------------------|------------------|
| January 2011   | 132.2                               | 132.3                                | 0.1              |
| February 2011  | 137.9                               | 137.5                                | -0.4             |
| March 2011     | 161.6                               | 161.2                                | -0.3             |
| April 2011     | 146.5                               | 146.7                                | 0.2              |
| May 2011       | 151.7                               | 151.8                                | 0.1              |
| June 2011      | 153.6                               | 153.5                                | -0.1             |
| July 2011      | 144.0                               | 144.0                                | 0.0              |
| August 2011    | 150.6                               | 150.2                                | -0.4             |
| September 2011 | 171.4                               | 170.8                                | -0.6             |
| October 2011   | 164.8                               | 164.8                                | 0.0              |
| November 2011  | 165.4                               | 165.0                                | -0.4             |
| December 2011  | 154.2                               | 154.1                                | -0.1             |

Source: CSO monthly bulletins.

The Polish consumer price index (CPI) is also subject to revisions – in this case, unlike the index of general business conditions and the index of sold industrial production, planned and regular. In March, the Central Statistical Office publishes revised values for January CPI in order to account for changes of weights in market basket of consumer goods and services. In March 2005, new methodology with weight structure based on data gathered in 2002 National Census was introduced (see National Bank of Poland and Monetary Policy Council 2006, p. 11).

## 6. Data revisions and testing of expectations

In section 3.3, the brief review of literature on influence of data revisions on macroeconomic forecasting has been presented. Let us address this issue for a special kind of forecasts – expectations of economic agents. I propose to define expectations as forecasts that are judged reliable and accurate enough to form basis for decision making (see Tomczyk, 2011). The following issues call for further study:

1. Since many (perhaps even the majority of) expectations time series are gathered through qualitative questionnaires, which data vintage should be used in quantification procedures? After all, preliminary values available to economic agents may be ‘guesstimates’ that will be later

found to be significantly different from revised (final) values, but these are all the agents have when they form their expectations.

2. Which data vintage should be used in evaluating accuracy of expectations? Zarnowitz & Braun point out that 'the final data may be issued years after the forecast was made and may incorporate major benchmark revisions. That the forecasters should be responsible for predicting all measurement errors to be corrected by such revisions, is surely questionable' (1992, p. 19).

So far, neither extent of data revisions nor their influence on quantification procedures or evaluating predictive properties of expectations were analysed in Poland, and were rarely addressed in world literature. As far as I am aware, only a few papers were published on sensitivity of aggregated expectations time series to data vintage.

Croushore (2006a) evaluates inflation forecasts from the Livingston Survey and the Survey of Professional Forecasters using the real-time data by examining the magnitude and patterns of revisions to inflation rate. He finds that 'the use of real-time data also matters for some key tests on some variables. If a forecaster had used the empirical results from the late 1970s and early 1980s to adjust survey forecasts of inflation, forecast errors would have increased substantially' (p. 1). He points out that revisions from initial release to each of the final versions of data (actuals) tend to vary substantially, and that evaluation of expectations errors is sensitive to the choice of actuals.

In a later paper, Croushore (2012) directly addresses the issue of rationality of expectations in presence of data revisions. More precisely, he examines whether tests of unbiasedness of expectations based on the Survey of Professional Forecasters are sensitive to changes in methodology, selection of subsamples and revisions of macroeconomic data used for evaluation of expectations. He finds that 'the results of bias tests are found to depend on the subsample in question, as well as what concept is used to measure the actual value of a macroeconomic variable' (p. 1), and that whether bias is found in survey forecasts heavily depends on data vintage selected for analysis. He describes revisions as 'significant', 'persistent' and 'nontrivial in several aspects'.

Arnold (2012), on the basis of extrapolative and adaptive models of expectations formation built for individual expert (professional forecasters) data, finds that there are no significant differences in expectations formation processes for the latest revision and for the initial values.

On the basis of literature presented above and mixed results found therein I believe that three main issues arise when data is revised in context of analysis of expectations.

First, in regard to process of expectations formation, which data are used by economic agents to formulate expectations: end-of-sample (that is, final) or data available in real time, or perhaps some intermediate values published between the first and final announcements? Do economic agents expect data revisions when forming their expectations? Do they consider real-time data to be reliable, and do EoS and RTV series differ with respect to reliability?

Second, when evaluating quality of expectations and their accuracy with respect to observed values, should RTV or EoS data be used? Which of these types of data should be employed to assess expectations (forecast) errors?

Third, should RTV or EoS data be used for the purpose of quantification of survey data on expectations? Quantification methods (both probabilistic and regression-based) require that survey data on values observed by respondents be compared with ‘official’ quantitative data series – but should they be end-of-sample or real-time data?

Two general suggestions were offered in my earlier publication (see Tomczyk, 2011):

1. When designing quantification models, survey data should be compared with final (EoS) data. Respondents are probably aiming to describe error-free final values and not initial ‘guesstimates’, subject to adjustments.
2. When evaluating accuracy of expectations of economic agents, particularly whether all information has been employed (so-called orthogonality tests), RTV data (that is, available at the moment of expectations formation) should be used, even if they were later corrected. Expectations should not be evaluated by comparison with final values because economic agents, at the time of their formation, did not have access to revised data, or to information that would enable them to assess the extent of revisions (unless they are predictable which has not been proved for Polish data).

As the review of literature presented in Section 3 shows, there is no shortage of literature on effects of data vintage on modeling and forecasting economic phenomena. However, the majority of papers is based on highly aggregated macroeconomic variables like GDP and money stock, and analyse data revision issues in the framework of fiscal or monetary policy. One of the reasons for such a focus may be importance of fiscal and monetary policy design and evaluation for practical purposes. Another reason, however, may be that key macroeconomic data is subject to major and systematic data revisions due to the high level of aggregation and numerous difficulties in reporting. Those factors cause initial data to be frequently revised and open a window of opportunity for researchers interested in studying data revisions. Less

aggregated variables – for example, monthly or quarterly series on industrial production, prices, or employment – are very rarely, if ever, analysed for issues associated with data vintage. I would like to propose to extend analysis of data revisions to less aggregated data, keeping in mind that specialised datasets will have to be constructed for this purpose.

As the second sub-field of data revisions analysis I would like to suggest the following topic: whether – and if yes, how strongly – results of quantification procedures and rationality tests are influenced by data vintage. Tests of rationality of expectations in Poland have failed to provide conclusive results, and neglecting data vintage issues may be one of the reasons for lack of unambiguous conclusions.

To summarise, I would like to propose that effects of data vintage be analysed from the point of view of properties of expectations series as explanatory variables in econometric models, quantification procedures employed for survey data, and rationality of expectations. Instead of focusing on highly aggregated macroeconomic variables, less aggregated monthly data should be used for this purpose. There are several reasons for this choice of dataset, among them longer time series, avoiding the problem of different sampling frequency for various variables, and possibility of comparative analysis, since previous research on properties of expectations in Poland was based, in significant part, on monthly data.

There are two additional advantages of employing monthly – and, consequently, relatively long – time series. First, cointegration techniques can be used, and long-term equilibrium between original and revised time series sought. Second, availability of a large sample enables the researcher to test properties of expectations in subsamples, and draw conclusions about, for example, sensitivity of expectations formation processes or quantification procedures to external shocks or phases of economic cycles. In the data revision framework, it is possible that behavior of variables in later (that is, based on more current data) subsamples differs from early subsamples because of difficulties associated with introducing adjustments in quality of goods and services (so-called hedonic adjustment). Landefeld & Grimm (2000) show that close to 18% of GDP in the United States is deflated by hedonic measures, that is, quality-adjusted prices are used. Since hedonic adjustments to already published data can be classified as data revisions, another field of research opens for economists interested in effects of data vintage on modeling economic processes.

## 7. Final remarks

The purpose of this paper was twofold: to present a review of literature and databases available for the purposes of real-time analysis, and to propose a framework for future research of effects of data vintage on properties of expectations. While empirical analysis of influence of data revisions on expectations time series is currently under way, there are three related projects which are also worth attention:

- analysis of predictability of data revisions in Poland;
- determining a number of periods after which there is no further (non-spurious) revisions to data series; this number may differ with respect to type and frequency of data;
- developing real-time datasets with Polish macroeconomic data for the purposes of further analysis of data vintage effects.

I believe that analysis of data revisions may help describe properties of expectations and improve quantification procedures and rationality tests, and therefore enhance our understanding of behaviour of economic processes.

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