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Preface

This paper proposes a new quality measure for macroeconomic statistical variables. The idea is simple, but hopefully the measure will provide a numerical device to assess how useful a statistical variable is. The measure is composed of forecast errors and revisions, and builds on earlier work by the author: a forecast accuracy study, Öller and Barot (2000) and a study of revisions, Öller and Hansson (2004). The latter was a project of Statistics Sweden in 2002.

This paper can also be seen as a continuation of the work on statistical quality published by Statistics Sweden in MIS1994:3 and MIS2001:1.

Lars-Erik Öller

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An ignorance measure of macroeconomic variables

Abstract: A measure is presented that could be said to reflect the quality of a macroeconomic statistical time series. The measure is a combination of how predictable the series is and how much its statistics needs to be revised. An "ignorance window" provides a snapshot of the quality, and may signal that a statistical variable is worthless.

Key words: Statistical quality; Forecast errors; Revisions

JEL Classification: E01

1. Introduction

Macroeconomics should become more useful to the policy maker if models and data improve. The philosophical abstractions can then be tested against reality in econometric models using empirical counterparts of theoretical variables. But do we know today how well statistical time series really reflect what they are supposed to? Can we measure the user quality of e.g. the National Accounts?

Data quality is generally expressed verbally in terms of contents, accuracy, timeliness, comparability, availability and clarity[1]. It is difficult to turn these properties into numerical measures, and even harder to aggregate them into one figure. Here and attempt is made to express the quality in one single measure. But instead of starting from the components, an implicit shortcut is chosen: measure how early and how accurately the public knows the value of a macroeconomic variable. This encompasses the verbal quality concepts listed above and can easily be measured.

There are three categories of studies that endeavor to measure some quality properties of statistical variables. One is to calculate how good their *forecasts* are. If a policy maker has a very faint idea about the value of a relevant variable next year, how is s/he to make a decision today that takes effect in the future? Research has focused on assessing the forecast accuracy of macroeconomic variables, especially since the *International Institute of Forecasters* was founded in 1981. A recent study of European macroeconomic forecast errors is Öller and Barot (2000). Fildes and Stekler (2002) is a more general discussion on macroeconomic forecast accuracy.

Another numerical approach to data quality is to look at *revisions*. Assuming honest and diligent statisticians, the number and amount of

[1] According to the quality guidelines in Statistics Sweden (2001), which in turn reflect recommendations of international organizations such as IMF and Eurostat. The UK Office of National Statistics has recently published "Guidelines for Measuring Statistical Quality", focusing on survey outputs. The report can be downloaded from www.statistics.gov.uk. An extension to National Accounts is likely in future versions. Survey quality is also the topic of Biemer and Lyberg (2003).

revisions reflect the reliability of a statistical variable. If its value has to be fundamentally changed as late as a couple of years after the event, how reliable are then the first (and most important) figures published, and how relevant is the last ex post figure to the policy maker? Can anybody be expected to forecast a variable that keeps changing its value ex post? A study on revisions of Swedish National Accounts expenditure variables is Öller and Hansson (2005)[2]. Following a line of research initiated by Mankiw and Shapiro (1986), Swanson and van Dijk (2002) study the *rationality* of revisions, another measure of ex post quality. They estimate the time it takes before a data vintage becomes rational, in the sense of Muth (1961).

A third way to measure a quality aspect of a statistical variable (in levels) is to analyze the values of successive vintages for common unit roots. This approach compares vintage estimates to repeated sampling, where the sample size is successively increased. Consistent estimation leads to convergence of sample estimates to the true population value. Analogously, successive vintages would have the same common trend, and this trend would then be close to the trend of the values of the final vintage. Interesting results can be found in Siklos (1996) and Patterson and Heravi (2004) for US data, Patterson (2002) for UK data, and Öller and Hansson (2005) for Swedish data. This approach will not be further pursued here.

"The process of estimating GNP starts with forecasts made many years before a quarter has begun and continues for years after it has ended". These words from McNees (1989) are the starting point of the quality measure presented in this study. An answer is given to the question: "How accurately can a statistical variable be estimated within a reasonable period of time? " If little is known about a statistical variable ex post and even less ex ante, the series is of doubtful practical use, and vice versa. Here, quality is understood precisely as *usefulness,* an attribute that encompasses all the verbal quality desiderata mentioned above. Useful data help a person to understand and to act accordingly. The opposite means that the data leave the user in ignorance. The measure introduced here is called *Ignorance*. It is simply a combination of forecast errors and revisions. Both of these suffer from the fact that the correct outcome is unknown. Here, the last vintage is taken to represent that value, but a hint is given for when this may not be a tenable assumption.

A 19th century economist had little numerical knowledge of the economy, simply because there were no National Accounts statistics, although many of the variables were defined as philosophical abstractions[3]. This could be labeled total (data) ignorance. Our efforts to record and understand the activity in the economy should have improved our knowledge, but how much ignorance is left today? Another question that can be answered by

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[2] Studies of US National Accounts revisions include Morgenstern (1963), Stekler (1967, 1987), Young (1974, 1995), Mork (1987), deLeeuw (1990) and Fixler and Grimm (2002).

[3] Many economists worked on building a mathematical and empirical structure for economics similar to that of physics. Statistical data would have to substitute for experimental. A System of National Accounts was eventually introduced in 1953, an accomplishment for which Sir Richard Stone was awarded the 1984 Prize in Economic Sciences in Memory of Alfred Nobel.

the ignorance measure is: are we more ignorant about variable *x* than about variable *y*?

In the next section *Ignorance* is defined and explained. In Section 3 two numerical examples are presented, and Section 4 discusses the new concept.

2. A measure of ignorance

Only by understanding a process can it be forecasted properly. Vice versa, if a process can be accurately forecasted it must have been understood.

The first part of the statement is necessary but not sufficient. A stock market time series is understood to be close to a random walk. Yet, generally, the best forecast is the naïve latest value. The latter part needs not always be true. Good luck may sometimes result in a wild guess being correct, but without knowledge of the process it is not possible on average to beat some naïve-forecasting rule.

In this sense forecast accuracy reflects how well the process is understood. Part of the data generator is explained by economic theory and the other part is the work of statisticians compiling the data according to the definitions laid down in that theory. If the theory is inadequate the measurements become meaningless, and if the produced measurements are of poor quality, what is understood theoretically is not reflected in the data and the empirical model collapses. Both deficiencies would lead to bad forecasts, but probably also to a measurement process that has to be repeated over and over again, with no guarantee of convergence between measurements. This process could also lend itself to a Bayesian interpretation, where theory, experience and historical data would form the prior, which is updated when preliminary data accrue.

These arguments support the use of forecast errors and revisions to measure the quality of a statistical variable. The construction of such a measure is the next task.

Assume given a stationary time series:

$$y_{lt},\ l = 1,\ldots, L;\ t = 1,\ldots,T\ .$$

For every t the measurement is made L times. Following Croushore and Stark (2001), we call l a V*intage.* The values of the first vintages are forecasts, the subsequent ones are outcomes. The observation y_{1t} is called the *First Forecast*. There is an observation $y_{t\lambda},\ 1 < \lambda < L,$ which is the first estimate (outcome) based on data from the whole period t **.** This is called the *Preliminary Figure*. The last estimate of period t, y_{Lt} ,is called the *Final Figure*.

Measurements y_{lt} are successive estimates of an unknown variable η_t , t = 1,…, T**.** The estimation process is stopped at Vintage L. Under the assumption that the estimates converge toward η_t, in empirical studies y_{Lt} is chosen as a substitute for η_t. The accuracy of Vintages can be measured by *Root Mean Square Error (RMSE)* :

$$RMSE_l = \sqrt{\frac{1}{T}\sum_{t=1}^{T}(y_{lt} - y_{Lt})^2}, l = 1,..., L. \qquad \langle 1 \rangle$$

These values are here standardized by the standard deviation of the Final Figures:

$$\overline{\boldsymbol{RMSE}}_l = \frac{\boldsymbol{RMSE}_l}{\boldsymbol{s}_L}, \boldsymbol{l} = 1,..., \boldsymbol{L},$$

where $RMSE_0 = s_L$.

The estimate s_L is assumed to be close to the true but unknown standard deviation $D(\eta_t)$. As in the Theil Measure, a value of the standardized *RMSE* at or above unity indicates a worthless forecast or preliminary figure, because the arithmetic average of historical values would be at least as accurate.

We will study the revision history of a variable over time, as measured by

$$\overline{\boldsymbol{RMSE}}_1, \overline{\boldsymbol{RMSE}}_2,..., \overline{\boldsymbol{RMSE}}_L,$$

where now by definition

$$\overline{\boldsymbol{RMSE}}_0 = 1, \boldsymbol{RMSE}_L = \overline{\boldsymbol{RMSE}}_L = 0$$

according to (1). A natural desideratum of convergence of Vintage estimates will then be satisfied trivially. Moreover, one would wish the convergence to be uniform, and fast in the beginning of the process, i.e. convex. A non-uniform convergence would mean that estimation errors become larger between two successive vintages. This could happen if data accumulating in the process are so bad as to be misleading, so that a forecast or a preliminary figure is revised in the wrong direction. Concavity indicates that fast convergence occurs only in a late stage of the estimation process, raising suspicion concerning the reliability of the Final Figure. If not even that figure would be close to the unknown η_t, then actually nothing would be known about that variable.

A square, called *Ignorance Window*, will illustrate the new concept. First, define a Vintage interval (l_1, L) during which the value of the variable is relevant for the decision maker. OECD starts forecasting the economies late in year t -2 for year t, so that one may choose $l_0 = t - 3$. We assume that at this point nothing is known about y_t except estimates of expected value and dispersion, as well as general knowledge about how the economy works. This situation is shown in Figure 1, illustrating a case of *Total Data Ignorance*, ex ante[4].

Figure 1
Total Data Ignorance, ex ante

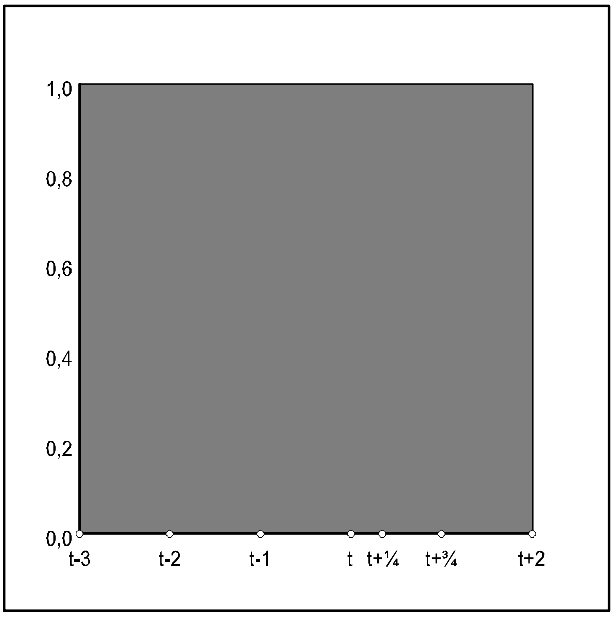


Figure 2
Ignorance, ex post

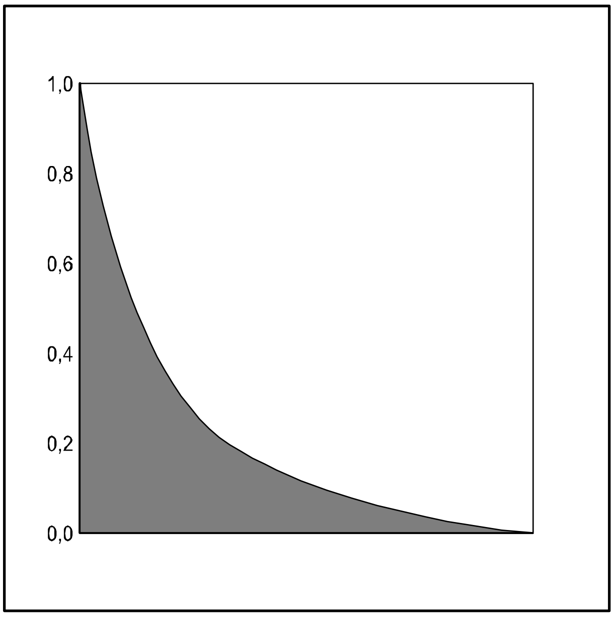


Figure 2 shows how ignorance about η_t could decrease as time passes and more data accumulate. We define the black area under the curve as *Ignorance* ***S*** about η_t. Ideally, correct information would accumulate continuously, and ***S*** would then be the integral of the curve. In practice we

[4] For a value above unity it is suggested to substitute unity, so as to keep the graph of a unit square.

measure a linear approximation with kinks where new information becomes available. The value of ***S*** can be calculated using numerical integration:

$$S = \frac{1}{2}\sum_{l=0}^{L-1}(\overline{RMSE}_l + \overline{RMSE}_{l+1})h(l, l+1),$$

where $h(l, l+1)$ is the length of the time interval between Vintages l and $l+1$. If the Vintages arrive at equidistant intervals $h(\cdot) \equiv h$, and without loss of generality one can set $h = 1$, so that

$$S = \frac{1}{2}\sum_{l=0}^{L-1}(\overline{RMSE}_l + \overline{RMSE}_{l+1}).$$

Next, define a standardized *Ignorance Measure* $\hat{S}$ by dividing ***S*** by the length of the whole estimation period $h(0,L)$, which for equidistant intervals can be set to unity. Then:

$$\frac{1}{2L} \le \hat{S} = \frac{S}{L} \le 1 - \frac{1}{2L}.$$

Here the lower limit is the case when the First Forecast and all successive estimates are identical to the Final Figure. If the upper limit is reached, total ignorance prevails until the Final Figure is published. The two extremes are shown in Figures 3 and 4.

Figure 3
Minimal Ignorance, $\hat{S}$ = 0.1

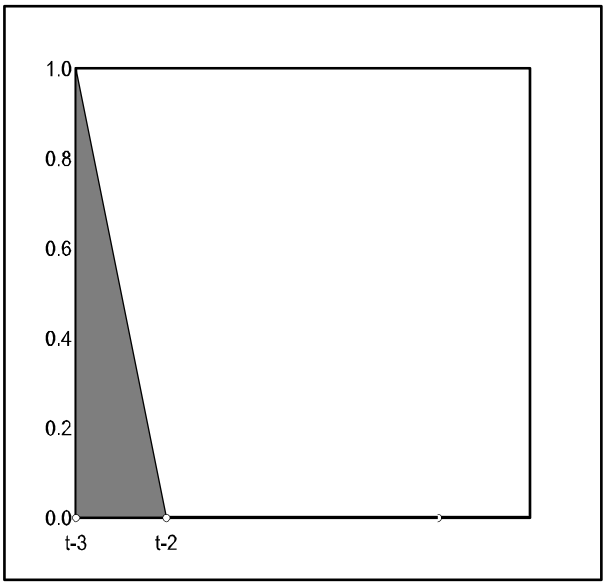
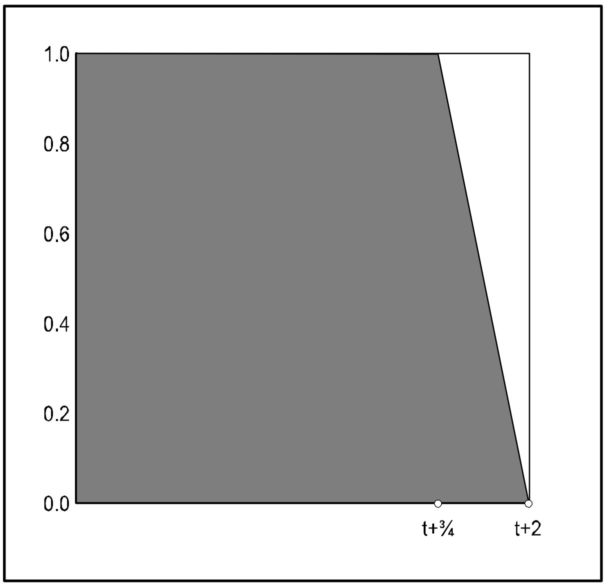


Figure 4
Maximal Ignorance, $\hat{S}$ = 0.9



3. An example

In order to illustrate the new concept, I have chosen two variables from the annual Swedish National Accounts: *Investments* (gross new capital formation), and *Central Government Consumption*. They are measured as annual growth rates. The forecasts are made by the National Institute of Economic Research, Sweden, in December[5] year t-2, t-1 and t. The statistical figures published by Statistics Sweden are from March and December year t+1 and December t+2. Hence L = 6, but intervals are not equidistant. During these five years, a user should be able to form a good idea of the numerical value of the variable in question. If not, it is doubtful whether there is any point in defining such a variable and compiling "statistics" on it.

Figures 5-6 present the Ignorance Windows of the two time series. The darker the window, the greater is Ignorance. Unity has been substituted for standardised *RMSE* values that exceed this limit. The curves start in t-3 when no forecast is available, which is interpreted as if nothing were known about the variable. In fact, since we are looking at stationary growth rates, the distribution can be estimated from past data, and hence estimates of the mean and variance are available at t-3, and the mean would be a (default) forecast. This could be adjusted using any theoretical or other a priori conception about the economy. We assume this prior to be flat, because nobody has been able to improve on naïve forecasts for that long horizons.

[5] Before 1986, only forecasts made in September are available. Two-year-ahead forecasts start in 1990.

Next, note in Figure 5 that the curve stays at unity when it reaches t-2, where the first forecast is published. This means that there was no point in forecasting investments two years ahead; the mean would have done the same job. Subsequently the curve declines fast, with a distinct kink where the Preliminary Figure succeeds the last forecast. Note, however, that both for forecasts and revisions the curves are concave, reflecting some lingering uncertainty.

Figure 6 looks very different. Central Government Consumption has a standardised *RMSE* slightly below unity for the first forecast at t-2. But when more statistical data become available at t-1, the curve is back at unity, and stays there to December year t when statistical data are available for 3/4 of the year! A probable reason to this strange behavior is that the preliminary (quarterly) data are so bad as to mislead the forecaster to revise in the wrong direction. If s/he would have stuck to the first forecast at t-2 the error would on average have been smaller, even at the end of year t. And, indeed, the revisions are huge. This comes close to making the statistical variable worthless. If so large revisions are needed all the way to t+2, how do we know that the need for revision stops there? Hence this is almost the situation in Figures 4 and 1. The ignorance measure is given in the diagrams, and also in Table 1.

There is a risk in rejecting a variable with a Window of Ignorance close to Figure 4. All estimates of the variable could be based on close to worthless quarterly data up to the Final Figure, which could be a reliable compilation of almost exact annual reports. But then, forecasts from such reliable two-year-old data should contain some information, blurred only when the bad data accrue. In such a case, only the data gathering process before t +2 should be rejected, but not the Final Figure statistics. On the other hand could the figure at t +2 be viewed upon as the data quality offered by a benchmark statistical office that produces just one statistical figure and publishes it two years after the event, which in practice would render real time forecasting nearly impossible.

The relationship between revisions and forecast errors becomes obvious by dividing the revision area by the forecast area. This is shown in the last row of Table 1. The smaller the revisions are as compared to the forecast errors, the smaller is Ignorance. This emphasizes the fact that bad data are hard to forecast.

Table 1
Ignorance measures

	Investments	Central Govern. Consumption
Ignorance $\hat{S}$	0.54	0.81
Revision/Forecast	0.12	0.36

Figure 5
Ignorance in Investments, $\hat{S}$ = 0.54

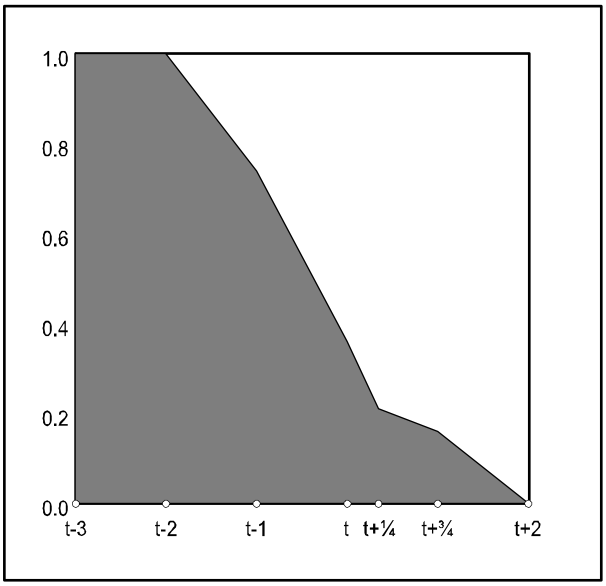
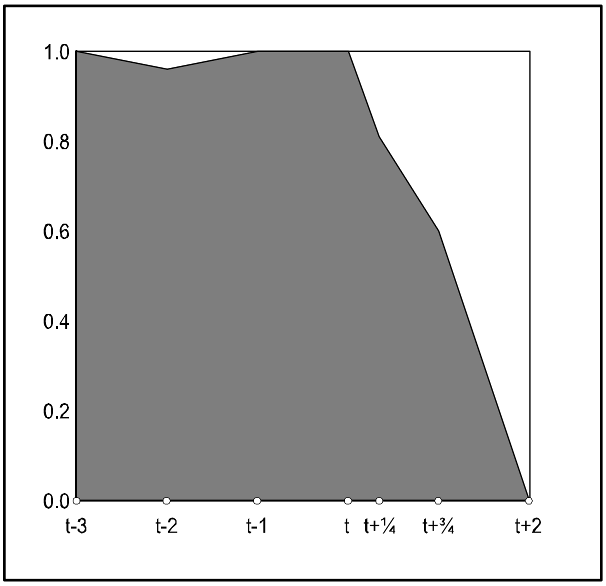


Figure 6
Ignorance in Central Government Consumption, $\hat{S}$ = 0.81



4. Discussion

A numerical measure has been presented that can be said to reflect the quality of a statistical variable. A graphical device, the "Window of Ignorance" shows how ignorance about a statistical variable decreases over time. The darker the window, the greater the ignorance. The measure can be used for deciding if it is meaningful to forecast a variable a certain amount of steps ahead, or to record it statistically at all.

It could be reasoned that the Window of Ignorance should consist of steps instead of straight lines connecting the points where figures are published, because it is only after the publication that they become public knowledge. Here, the straight lines symbolise a process of decreasing ignorance before publication, approximating a continuous process, as in Figure 2. But steps may in certain situations be more realistic. If the change in a stock exchange variable were regarded as unpredictable, complete ignorance would prevail to the very moment when the statistics is recorded and published online, after which ignorance would be identically zero, because such data do not need to be revised. The window would then consist of a black and a white rectangle, and if forecast and revision periods would be of equal length, Ignorance $\hat{S}$ would be 0.5. The same value would occur for a variable with a linear decrease of Ignorance along the diagonal of the window, the border case between convex and concave curves.

In the example, only six forecasts/preliminary figures were recorded, demonstrating the main features of the proposed measure. Both forecasts and revisions are generally made more often, and the time scale could then be made finer. For such data, one may expect that forecasts and preliminary figures often are revised in the wrong direction, as happened in Figure 6 at t-1. Studying the revision history of U.S. monthly Industrial Production, Swanson and van Dijk (2002) found that the first revision during recession months pushed the second release further away from the final figure. Cho (2002) presents evidence that preliminary figures improve forecasts of some US financial data, but not of US GDP growth and inflation forecasts. This again highlights the relationship between preliminary figures and forecast convergence.

The choice of forecasting agency may be controversial. In the example, the best-known forecaster in Sweden was chosen. Other possible choices are: the agency with the significantly best forecasts during the past T years, or pooling forecasts of major agencies.

Ignorance is intended as an overall measure of quality. But it does not cover all aspects of data quality. Rationality and common trend tests are useful complements, not yet mentioned in official lists on quality concepts.

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