Signal Extraction from the Philippine National Accounts Statistics using ARIMA Model-based Methodology

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The state of the art in signal extraction gradually evolved from the use of a mechanical form of moving average filters to the present sophisticated model-based techniques capable of performing automatic modeling and signal extraction involving hundreds or even thousands of time series in one production run. The leading edge of technology is being shared by two ARIMA model-based systems: ARIMA X12 of the US Bureau of Census and the twin programs TRAMO-SEATS developed at the Bank of Spain. These specialized expert systems have been adopted by most statistical agencies of advanced OECD countries and the European community. The Philippines on the other hand is using the ARIMA X11 system modified by the Bank of Canada in its routine seasonal adjustment and time series decomposition tasks. This study is an attempt to implement the ARIMA model-based (AMB) approach of extracting unobserved signals from 194 quarterly national accounts statistics of the Philippines using the TRAMO-SEATS system in a fully automatic modeling mode. The successful result of the application adequately demonstrates the feasibility of adopting a system being used routinely by countries in more advanced economies.

INTRODUCTION

The set of macroeconomic variables, comprising the country's national accounts statistics is one of the most eagerly monitored databases anywhere. Economists, financial analysts and other social scientists keenly watch the movements of the components of the gross domestic product (GDP) to make their prognostications on the health of the economy over time. Economic growth is frequently equated to sustained upward movements of the real gross domestic product and its main component parts while spells of stagnation, or even recessions have been indicated by down trending movements of the real aggregate GDP and most of its various components. Accurately anticipating the future magnitudes and directions of these macroeconomic variables as well as deriving from them relevant predictive signals has become a major requisite of effective fiscal and development planning.

Forecasting macroeconomic variables is one of the most fruitful applications of time series econometrics. In the light of ever-improving coordination among data monitoring and collecting agencies, more reliable and timely statistics of varying periodicities have become readily available to researchers than ever before.

This development, coupled with the widespread availability of cheaper yet powerful computational devices and advances in information technology have been narrowing the gap between the theory and practice of economic forecasting. As the state-of-the-art in time series econometrics rapidly unfolds, analysts can now effectively extract additional predictive information from available sub-annual macro variables, creating more value to the forecasting task. The study is an attempt to apply the current modeling technology (which is now standard in most western countries) to the different components of the country's gross domestic product and other quarterly national accounts statistics. The goal is to ascertain the plausibility of adopting a leading-edge model-based forecasting and signal extraction methodology to isolate unobserved signals from the available series that may be of utmost interest to a wide variety of analysts and planners.

The rest of the paper will be organized as follows: a general discussion on the evolution of the ARIMA Model-Based (AMB) approach in signal extraction and forecasting, focusing on the technique currently being used by Eurostat and other major data agencies worldwide - TRAMO and SEATS; the database of the study is described next, highlighting the statistical properties and stylized facts on the variables. The operational framework will tackle the technical details of the models to be used and then the portion on the actual empirical modeling will immediately follow, culminating in the presentation of the results of the modeling effort. Concluding remarks and recommendations will end the study.

THE ARIMA MODEL BASED (AMB) SIGNAL EXTRACTION FROM UNIVARIATE SERIES

The observed realization of a time series variable has been thought to consist of unobserved, but intuitively appealing components (which in this study are collectively referred to as signals) – secular trend (τ_t), cyclical fluctuations (C_t), seasonal variations (S_t) and irregular variations or noise (ε_t). Secular trend represents the upward or downward movement of the data over a long period of time, generally associated with the underlying structural causes of the phenomenon; seasonal variations represent the pattern of changes in the data that completes itself within a calendar year which are mainly the effects of climatic and institutional events that repeat more or less regularly every year; cyclical fluctuations (popularly called business cycle), are characterized by upward and downward changes in the data pattern that occurs over the duration of 2 to 10 years or longer mainly due to fluctuations in economic activity and then finally, the noise – the erratic movements of the data that have no predictable pattern.

The conventional practice in applied time series analysis relies heavily on the use of moving average filters to extract these unobserved signals from macro variables. Some of the most popular techniques are the Classical (multiplicative or additive) Decomposition (in isolating, τ_t, C_t and S_t), the Census X-11 method of seasonal adjustment and the Hodrick-Prescott (1997) filter of extracting the business cycle. Over time however, the application of these mathematically elegant but basically ad-hoc filtering methodologies manifested various limitations, most of which stem from the fixed nature of the signals, wherein underestimations or overestimations are likely to occur.

An alternative approach was suggested by Cleveland and Tiao (1976) and Burman (1980) whereby filtering is accomplished by a statistical model called ARIMA (Autoregressive Integrated Moving Average) model introduced earlier by Box and Jenkins (1970). The approach known as the ARIMA model based (AMB) technique consists of a two-pronged strategy: first, an appropriate ARIMA model is fitted to the observed time series, and second, signal extraction techniques are employed to isolate the unobserved components of the series with filters that are in certain well-defined ways optimal.

Among the different AMB methodologies that achieved widespread use is the SEATS (*S*ignal

*E*xtraction in *A*RIMA *T*ime *S*eries) developed by Bank of Spain mathematicians Gomez and Maravall (1996). Signal extraction by SEATS presupposes the prior cleansing of the raw data and the development of a highly desirable ARIMA model of the pre-treated data. Cleansing requires corrections or adjustments to account for certain factors that distort the inherent patterns of the data. These factors are classified into three categories: outliers (additive outliers, level shifters and transitory changes), calendar effects (trading day, Easter effect, leap year effect, holidays); and intervention variables (strikes, devaluations, natural disasters, political events, etc.).

Data cleansing and the development of the optimal ARIMA model is accomplished by the companion program to SEATS called TRAMO (*T*ime series *R*egression with *A*RIMA noise, *M*issing observations and *O*utliers). The two programs are traditionally considered as just one expert system known worldwide as TRAMO-SEATS.

TRAMO-SEATS can handle efficiently, in an automatic manner, applications to a single series or thousands of series making it extremely suitable for production use by data monitoring and producing agencies, policy making institutions, private think-tank groups and business firms. Its most widespread use is in seasonal adjustment. These two programs are virtually fused; with the latest version residing within Tramo Seats for Windows (TSW) – a Windows interface also developed at the Bank of Spain (Caporello and Maravall 2004, 2010). The objective of TSW is to estimate a seasonal ARIMA model and to decompose it into additive signal components; estimation is done by TRAMO and decomposition by SEATS.

REVIEW OF RELATED LITERATURE

The Evolution of the AMB Signal Extraction Approach

Although the traditional approach to model the unobserved components of time series variables has been generally attributed to Macaulay (1931), the practice of mathematically isolating predictive parts of historical data originated further back in history during the early part of the last century. It was noted that observed time series appeared to be coming from unobserved manifestations coinciding with well recognized events (from Bell & Hillmer (1992)) and ever since the idea has stuck. Early researchers concentrated on removing the trend and seasonal differentials from annual data (mostly production figures and prices) by averaging over several years or by freehand fitting of mathematical equations. Anderson (1914) introduced the fitting of linear and higher order polynomials to eliminate the trend component, thereby ushering in the era of "trend analysis". During the same period, economists (e.g. Henderson, 1916 and Flux, A.,1921) were active in trying to forecast the stages of the economic cycle by removing both the trend (via trend analysis) and seasonality (via averaging) from economic data to derive residual series that was seen to contain indications of cyclical changes. What appeared to be lacking during the era was a unified procedure or model that would link the various techniques of extracting these unobserved components.

A flurry of research activities was noted during the 1920s and the 1930s, precipitated by the work of Persons (1919) in the area of seasonal adjustment. His method called the "Link Relative Method" specifies an algebraic representation of a time series as a product of its (unobserved) component parts, that is:

$$X_t = S_t T_t C_t R_t$$

where S_t is the *seasonal component* T_t is the *trend component*, C_t is the *cyclical component* and R_t is the *random component* of time series X_t observed at time t. The Link Relative Method employs simple transformations to isolate T_t and S_t via averaging and the judicious use of running medians. The end products of applying the method are fixed estimates of the four components of the series.

THE CLASSICAL DECOMPOSITION METHOD

Macaulay (1931) improved on the Link Relative Method by employing both the curve fitting technique of Anderson (1914) to isolate the trend and an innovative approach called the Ratio-to-Moving Average method to extract the other components of the time series. The system proposed by Macaulay came to be known as the "Classical Decomposition Methodology" which is still being used extensively today by "traditionalists". The Macaulay approach also laid the ground works for many modern signal extraction systems including the extremely popular Census X-11 (Shiskin and Eisenpress 1958) and its successor Census X-12 (Shiskin, et al., 1967) methods.

Long after the introduction of the Macaulay method, two major developments came during the early 1950s. The first was the emergence of a wide array of exponential smoothing techniques which greatly simplified the rigorously repetitive computations needed to be performed earlier, and in addition produced estimates with remarkable forecasting performance. The second development was the introduction of computers thereby facilitating the forecasting and signal extraction tasks using the techniques of the era (Shiskin & Eisenpress 1958). This development also allowed researchers to develop even more intricate techniques, spearheaded by the Census I method (1954) which formalized the Macaulay (1931) ratio-to-moving average method into a computer amenable form with substantial enhancements. The Census I method was later modified to produce a more complex Census II method (1955). Both systems were developed by the U.S. Bureau of Census with technical and funding help from the National Bureau of Economic Research (NBER) (Shiskin & Eisenpress 1958).

Critical reviews of the Census II method revealed areas of improvement which eventually led to a sequence of progressively more sophisticated variants of the technique, resulting in the development of Census X-3 to Census X-10 methods. The high watermark level of these methods was reached in 1965 when the Census X-11 method was introduced, which to this day remains one of the most widely used seasonal adjustment programs worldwide. This modification of Census II also retained the use of the ratio-to-moving average procedure introduced by Macaulay (1931) and incorporated enhancements which included adjustments for trading day and other outliers, the use of efficient ad-hoc filters plus improved model options and output generation. The ad-hoc filters cleanse or adjust the series from the variance which falls in a certain band around the frequencies regarded as noise. After its introduction in 1965, many statistical agencies around the world adopted the technique, it soon became a mainstay tool in various econometric softwares.

THE MODEL-BASED APPROACH TO SIGNAL EXTRACTION

The modern approach to time series analysis can be traced back to Yule (1927) who introduced the autoregressive models and to Slutsky (1937) who proposed the moving average models. But it was Wold (1938) who started the application of these models to actual data and also described the mixed ARMA models. The application of the ARMA family of models was limited to a special type of time series data called *stationary series* which are not commonly encountered in practice. Furthermore, the computational aspect of estimating and diagnosing such models was enormously tedious using the facilities of the era; so that prior to the introduction of the computer, large scale application of such models was simply not feasible. These difficulties put major stumbling blocks for data producing agencies and researchers to use the ARMA modeling technology in the area of routine signal extraction and forecasting in their ever growing time series archives.

Following the publication of the work of Box and Jenkins (1970) on autoregressive integrated moving average (ARIMA) models of non-stationary time series, a new modification of Census X-11 method called X-11 ARIMA emerged. This variation of the X-11 method was developed by Statistics Canada (Dagum 1975, 1978, 1980) beating the U.S. Bureau of Census in launching a true model-based technique in the spirit of Cleveland & Tiao (1976) and Burman (1980). The introduction of X-11 ARIMA offered an attractive alternative to the ad-hoc filtering methods (which characterized the traditional approach) of signal extraction and forecasting, not only by its intuitive appeal but also because of its sound statistical underpinnings.

The Model-based approach to signal extraction provides a sound basis for statistical inference to be made on the non-observable components of the time series, allowing analysts to make appropriate diagnosis of the results. Properties of the estimates can be assessed and standard errors, as well as confidence intervals of the extracted signals can be properly established to reflect the inaccuracies with which these components are estimated. The necessity of measuring the precision of these estimates has been emphasized by experts for a long time (see Bach, et al., 1976 and Moore, et al., 1981).

The success of the X-11 ARIMA and that of the model-based technology provided a strong impetus to the U.S. Bureau of Census to come up with an AMB enhancement to the X-11 Census method. This resulted in the emergence of the X-12 ARIMA, which employed the basic X-11 ARIMA procedure but with certain alterations such as: implementation of the sliding span diagnostics for improved model-selection, an ability to efficiently process many series at once, and an entirely new revolutionary routine which handles data pre-treatment (to cleanse the data) prior to signal extraction. This pre-treatment routine has come to be known as the RegARIMA (Regression models with ARIMA noise) procedure which is designed to estimate calendar effects, extreme values and different forms of outliers via built-in or user-defined regressors. Estimation is undertaken by exact Maximum Likelihood technique (Findley, et al., 1998). Experimental versions of the X-12 ARIMA called X-13A-S and X-13A-T, which are fusions of the X-12 ARIMA and SEATS, and X-12-ARIMA and TRAMO respectively are currently being developed at the U.S. Bureau of Census in cooperation with the Bank of Spain and NBER (Findley, 2005).

The introduction of the model-based signal extraction system (particularly the AMB system) was received enthusiastically by the international research community and statistical data agencies, especially after numerous empirical studies (e.g. Gomez, V. & Bengoechea, P., 2000, Findley, et al., 1998; Depoutot & Planas, 1998; Hillmer & Tiao, 1982; and Kuiper, J., 1978) confirmed the relative superiority of the model-based approach over the traditional approach.

The widespread adoption of the AMB methodology encouraged model developers to come up with a wide range of alternative AMB systems to the standard X-12 ARIMA. These systems include the following: X-11 ARIMA/88 and X-11 ARIMA/2000 by Statistics Canada (Dagum, E., 1988), X-12 ARIMA UK Version (Thorp, J., 2003), TRAMO-SEATS by the Bank of Spain(Gomez, V. & Maravall, A., 1996), STAMP (Koopman, S., et al., 2000) by the Bank of England, DEMETRA by Eurostat (Eurostat 2002), SEASABS by Statistics Australia (McLaren, et al., 2006), DAINTIES by European Commission (Fok et al., 2005), SABL by Bell Laboratories (Cleveland, Dunn, & Terpenning, 1978) and BV4 by Federal Statistical Office of Germany (Cieplik, 2006 and Speth, 2006). Currently, the list of countries which use the X-12 ARIMA include the United States, United Kingdom, Canada, New Zealand, Japan, Israel, Argentina and other industrialized countries.

Among the current crop of model-based systems, the twin model developed at the Bank of Spain named TRAMO-SEATS has been receiving good reviews (e.g., Fok, D. et al., 2005; Pollock, D.S.G., 2002; Hood, C., 2002; Maravall & Sanchez, 2001; Gomez, V. & Bengoechea, P., 2000; Hood, C. et al., 2000; Albert, J.R., 2002; Monsell, B., et al.,2003; Scott, S. et al., 2007; and

McDonald-Johnson, K. et al., 2008), and it has an excellent capability of implementing automatic simultaneous modeling of, and signal extraction from, hundreds or even thousands of time series. Its aim is to implement a model-based procedure of seasonal adjustment and trend extraction that requires little intervention on the part of the user. TRAMO cleanses the data, then identifies and estimates the appropriate seasonal ARIMA model for each time series, as a prelude to signal extraction by SEATS via optimal filters such as the Weiner-Kolmogorov and Kalman filters.

In many ways, TRAMO presents similarities with the pre-treatment RegARIMA program of X-12 ARIMA particularly on the automatic modeling aspect. Current research undertakings involve the fusing of the X-12 ARIMA with TRAMO and/or SEATS to take advantage of the good features of the programs (Monsell, B., et al., 2003; Hood, C., 2002). The TRAMO-SEATS procedure is currently being used extensively by Eurostat for routine seasonal adjustment of thousands of time series produced by different European Union countries (Eurostat 2009).

SEASONAL ADJUSTMENT OF PHILIPPINE TIME SERIES

In the Philippines, the current official methodology adopted by the National Statistical Coordination Board (NSCB) is the X-11 ARIMA method (Bersales, L., 2010). The version of X-11 ARIMA employed by NSDB for production use is the X-11 ARIMA 2000 developed by Statistics Canada, mainly for routine seasonal adjustment tasks. The computation of seasonally adjusted time series in the Philippine statistical system commenced in 1992 under the technical assistance of Asian Development Bank, with Dr. Estela Bee Dagum of Statistics Canada as one of the consultants (Foronda, A., 2005).

The first Seasonally Adjusted National Accounts (SANA) was released in 1994, with the first quarter of 1988 as starting point. The SANA is now being published concurrently with the regular quarterly System of National Accounts (SNA). The national accounts series being seasonally adjusted and published are: Gross National Product (GNP), Agriculture, Fishery and Forestry (AFF) sector, Industry sector, Services sector, Gross Domestic Product (GDP) an aggregation of major sectors and Personal Consumption Expenditure (PCE) (Technical Working Group on Seasonal Adjustment of Philippine Time Series, 2007).

In 2002, a study (Albert, J.R., 2002) was undertaken by the Statistical Research and Training Center (SRTC) under the Re-engineering Philippine Statistical Services Phase II Project (Foronda, A., 2005), which explored the viability of applying X12 ARIMA and TRAMO-SEATS methods to some Philippine time series data. The study sought to consider, on the grounds of some empirical criteria, which procedure should be preferred for routine seasonal adjustment of Philippine time series. The conclusion was clear: “for the domain of Philippine time series studies, TRAMO-SEATS is recommended” (Albert, J.R., 2002).

The current study may also be considered as an attempt to provide an additional empirical basis for the recommendation of the Albert (2002) study on the judiciousness of the use of TRAMO-SEATS for routine large scale seasonal adjustment, forecasting and signal extraction involving the hundreds of time series being produced and maintained by the Philippine Statistical System.

MODELING FRAMEWORK

Under the ARIMA model-based approach, each of the quarterly national accounts time series will be depicted as being generated by a stochastic process driven by a host of deterministic factors and a SARIMA (Seasonal Auto Regressive Integrated Moving Average) type noise element. These factors, known as intervention variables are mainly classified into three categories: trading day (TD) effects - caused by the different distribution of weekdays in different months and captured by the number of trading days of the month the Easter effect (EE), which captures the moving dates of Easter in different years and Outliers – events which happen on certain months capable of shifting levels or directions of the time series. Outliers are further categorized into three different types: Additive Outliers (AO); Transitory Change outliers (TC); and Level Shift (LS) outliers. AO outliers are events that cause one-time spikes in the series; TC outliers create transitory changes; while Level shifters are shocks with permanent effects.

Symbolically, if Y_{it} is the observed value of the ith national account variable during quarter t, and D_{sjit} is a dummy variable that indicates the position of the sth event of the category jth outlier (i.e. AO, TC and LS, for the ith country during time t, and TD_t is the number of trading days in month t, and D_{EEt} = 1 if Easter occurs during time t, zero otherwise), the model can be specified as follows:

$$Y_{it} = \varphi_t + \psi_{TDt} TDt + \psi_{EEt} D_{EEt} + \sum_{j=AO}^{LS} \sum_{s=1}^{n_j} \psi_{sjit} D_{sjit} + D_{jit} + X_{it} \tag{1.1}$$

for the ith national account component, during time t. The parameter ψ_{sjit} is the effect of the sth event of the jth outlier type on the series during time t and X_{it} is a stochastic noise element (random error) that follows an $ARIMA(p,d,q)(P,D,Q)_{12}$ process for each country over time. Algebraically, the noise X_{it} is represented in lag polynomial form as:

$$\phi_P(L)\Phi_P(L)\delta(L)\, X_{it} = \theta_q(L)\Theta_D\, \varepsilon_{it} \tag{1.2}$$

where ε_{it} is a white noise innovation (i.e. i.i.d. with mean zero and constant variance); $\phi_P(L), \Phi_P(L)$, $\theta_q(L)$ and $\Theta_D(L)$ are finite lag polynomials in L (lag notation with the property $L^n y_t = y_{t-n}$). The first two contain respectively the p stationary regular AR roots and the P seasonal AR roots of; the last two are, respectively the q invertible regular MA roots and Q seasonal MA roots of X_{it}. Algebraically, these lag polynomials are specified as:

$\phi_P(L) = 1 - \phi_1 L - \phi_2 L^2 - \ldots - \phi_p L^p \;\rightarrow$ regular autoregressive lag polynomial

$\Phi_P(L) = 1 - \Phi_1 L^s - \Phi_2 L^{2s} - \ldots - \Phi_p L^{Ps} \;\rightarrow$ seasonal autoregressive lag polynomial

$\theta_q(L) = 1 - \theta_1 L - \theta_2 L^2 - \ldots - \theta_q L^q \;\rightarrow$ regular moving average lag polynomial

$\Phi_Q(L) = 1 + \Phi_1 L^s + \Phi_2 L^{2s} + \ldots + \Phi_Q L^{Qs} \;\rightarrow$ seasonal moving average lag polynomial

The lag polynomial $\delta(L) = (1-L)^d (1-L^s)^D = \nabla^d \nabla_s^D$ contains the d regular and the D seasonal unit roots of the noise component X_{it}. In this study s = 4 since data used is of quarterly frequency.

SUMMARY OF THE ESTIMATION AND INFERENCE PROCEDURES

The standard method implemented by the different well known signal extraction softwares calls for the pre-adjustment of the series prior to signal extraction (e.g. the reg-ARIMA component of Census X-12 and the TRAMO component of TRAMO-SEATS implement this initial step). This procedure is necessary to establish the estimated models (1.1) and (1.2) for each national accounts variable and its stochastic noise element, respectively. In this study, the twin programs TRAMO-SEATS will be used in implementing all computational aspects.

The pre-adjustment procedure (TRAMO) assumes initially that the noise follows the parsimonious default model known as the **Airline Model** (*ARIMA* (0,1,1)(0,1,1)$_s$ where s is the frequency of the series (s =12 for monthly and s = 4 for quarterly). The Airline Model is well suited for a large number of real-world time series (Box, G. and Jenkins, G., 1970) and has become the benchmark model in modern time series analysis.

The Airline Model is initially applied to the series and then pre-tested for the log-level specification using the Schwarz Information Criterion (SIC), sometimes referred to as Bayesian Information Criterion (BIC), as basis of choice. Once the decision to use either the level or log transformed version of series is reached, regressions are then run for the residuals of the default model to test for Trading Day (TD) and Easter (EE) Effects, after which an iterative procedure is implemented to identify the various outliers. This procedure iterates between the following two stages: (1) outlier detection and correction; and, (2) identification of an improved model. To maintain model's parsimony, model identification is confin ed within the following integral ranges: $0 \leq p, q \leq 3$ and $0 \leq P, Q \leq 2$ for the regular/seasonal autoregressive/ moving average orders and $0 \leq d \leq 2$, $0 \leq D \leq 1$ for the number of regular and seasonal unit roots respectively. Pre-testing for the presence of deterministic mean μ_i of X_{it} is also embedded significant, the X_{it} in (1.1) and (1.2) is to be replaced by its de-meaned value $x_{it} = X_{it} - \mu_i$.

Aside from testing the statistical adequacy of the parameters, the following diagnostic procedures will be implemented to handle the goodness-of-fit assessment of the alternative models for each series: the Ljung-Box (Q) test for residual autocorrelation; the Jarque-Bera (JB) test for normality of residuals; the SK and Kur t-tests for skewness and kurtosis of the residuals; the Pierce (QS) test of residual seasonality; the McLeod and Li (Q2) test of residual linearity; and the Runs t-test for residuals randomness. The Exact Maximum Likelihood Estimation (EML) procedure via Kalman Filtering is used in parameter estimation and inference. The Hannan-Rissanen (H-R) Method is used to get starting values for likelihood evaluation (Gomez & Maravall, 1996). See Figure 1 the schematic diagram of the Tramo-Seats procedure.

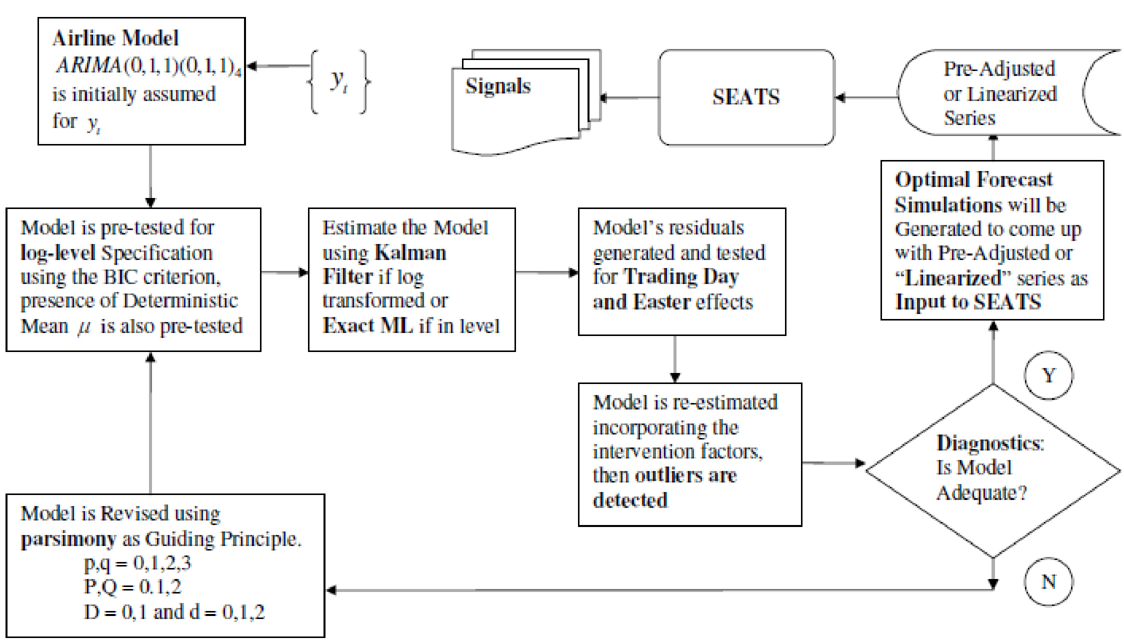

Figure. 1 The TRAMO-SEATS Procedure

The general Box-Jenkins iterative methodology is followed in modeling the noise element of each quarterly national accounts series. For each series, the iteration will go on until the best noise model is established for use in coming up with a linearized series from which signals are to be extracted. This resulting series has been adjusted for the influence of the calendar factors and outliers as well as the impact of missing observations, if there are any. In the TRAMO-SEATS system, signal extraction procedure is accomplished by the program SEATS.

SEATS was originally devised for seasonal adjustment of economic time series (i.e., removal of the seasonal signal); and the basic references are Cleveland and Tiao (1976), Box, Hillmer, and Tiao (1978), Burman (1980), Hillmer and Tiao (1982) and Bell and Hillmer (1984). Eventually, the program evolved into a full signal extraction system that decomposes a series which follows model (1.2) into several components. The decomposition can be multiplicative or additive; but since the former becomes the latter by taking logs, the additive model of decomposition provides a more universal way of presenting how the components are resolved. The components that SEATS considers are:

x_{pt} = the TREND component,

x_{st} = the SEASONAL component,

x_{ct} = the CYCLICAL component,

x_{ut} = the IRREGULAR component

If the pre-adjusted log-linearized series is x_t, then $x_t = x_{pt} + x_{st} + x_{ct} + x_{ut}$. The SEATS program estimates these components via the Wiener–Kolmogorov filter (Gomez & Maravall, 1996). Both TRAMO and SEATS programs can handle routine applications for a large number of series and provide a complete model-based solution to the problems of forecasting, interpolation and signal extraction for non-stationary time series.

APPLICATION OF THE MODELING FRAMEWORK

The interest of the study centers on a large scale application of TRAMO-SEATS to the various quarterly national accounts components of the Philippine Statistical System spanning the period from the first quarter of 1981 to the fourth quarter of 2010 (some of the series started only in the first quarter of 1991) . A Total of 194 quarterly time series comprise the subject matter variables in the study. Because of the sheer size of the data base, the automatic modeling capability of the program is heavily exploited in this study.

The first part of the program (TRAMO) estimates the possible outliers and calendar effects, which are treated as deterministic factors; and hence decomposes the observed series Y_{it} into a deterministic portion and a stochastic component. The first four terms of the Right Hand Side (RHS) of model (1.1) add up to the deterministic element of the series and is referred to as the "pre-adjustment" component; and once it is removed from Y_{it}, an estimate of the stochastic part X_{it} is obtained. This stochastic component (called the noise) is assumed to be the output of a stochastic process specified by model (1.2) and is also referred to as the "linearized series" (Gomez & Maravall, 1996).

In the second part of the program (which is the SEATS), the ARIMA-model-based (AMB) methodology is used to estimate the unobserved stochastic components (i.e, x_{pt}, x_{st}, x_{ct}, and x_{ut}) in the "linearized" series of X_{it} generated by TRAMO. Among these components, the seasonal (x_{st}) and the secular trend (x_{pt}) constitute the two most important signals to economists and policy makers; although in recent times, substantial interests are generated by the cyclical component x_{ct}. When the program determines that the identified model in the TRAMO portion is deemed unacceptable by the signal extraction criteria of SEATS, appropriate modification of the model will be implemented.

RESULTS

After establishing the input parameters needed by the TRAMO-SEATS system, the two programs are set in production (i.e., automatic modeling) mode and run using a Pentium Dual Core 3Gb RAM notebook computer. The TSW (TRAMO-SEATS for Windows) Version Beta 1.0.4 Rev 177 (June 2010) implemented the system. Total execution time is about 30 seconds. A sequence of matrices, graphs, and output series is generated from which the following results are derived.

TRAMO ANALYSIS

When Automatic Model Identification (AMI) mode is activated, all of the 194 quarterly series are simultaneously modeled using the procedure described earlier. Under this mode of operation, the most important output is the 8-worksheet matrix called "Out Matrix" for TRAMO analysis and the companion 3-worksheet matrix for SEATS analysis. For the TRAMO portion of the results, the primary worksheet exhibits the empirical noise model identified automatically by TRAMO for each series and the results of the various diagnostic tests performed to assess the statistical and econometric adequacy of the models. Out of the information presented in the worksheet a series of summary tables (Tables 1 to 4) were created to highlight the over-all results of the modeling process.

It can be seen in Table 1 that close to 87% of the series requires logarithmic transformation prior to modeling, with the rest being modeled in their level values. About 94% are deemed non-stationary, necessitating the extraction of regular/seasonal unit root(s). Only 6% are inherently stationary (integrated of order zero). About one in twenty (5%) series has no Airline model multiplicative seasonal structure (purely regular). For sixty-six of the series (34%), the default ($ARIMA(0,1,1)(0,1,1)_4$) proved to be the most appropriate noise process.

Among the non-stationary series, eighty seven (45%) require the $\nabla\nabla_4$ transformation (regular and seasonal differencing) for conversion into stationary series, with only 15 series (8%) need the ∇ transformation (regular differencing) while 80 series (41%) are required to undertake the ∇_4 transformation (seasonal differencing). No series turned out to contain more than one unit roots (regular or seasonal).Table 2 details the cross tabulation of the regular (d) and seasonal (D) unit roots.

Table 1
General Features of the Final Noise Models for the Series Identified by TRAMO

Model Features	Number of Series	Percent (%)
Levels	26	13.40
Logs	168	86.60
Regular Differenced	102	52.58
Seasonal Differenced	167	86.08
Stationary	12	6.19
Non Stationary	182	93.81
Purely Regular	9	4.64
Airline Model (Default)	66	34.02

Table 2

Breakdown of Series with Regular (d) and Seasonal (D) Unit Roots

Number of Series with	d = 0	d = 1	d = 2	Total
D = 0	12 (6.19%)	15 (7.73%)	0 (0.00%)	27 (13.92%)
D = 1	80 (41.24%)	87 (44.85%)	0 (0.00%)	167 (86.08%)
Total	92 (47.42%)	102 (52.58%)	0 0.00%)	194 (100%)

The features of ARMA parameters of the stationarized series are presented in Table 3. The average number of the ARMA parameters (regular and seasonal) is 1.64 implying the highly parsimonious nature of the models identified by TRAMO to characterize the noise process of the national accounts series. Most of the parameters are of the autoregressive variety (AR(1), AR(2) or AR(3)) with 49.48%, followed by the first order seasonal moving average (SMA(1)) with share of 43.30%. The least frequent ARMA parameter is the first order seasonal autoregressive (SAR(1)) which account for only 11.34% of the series.

The results of various diagnostic tests are presented in Table 4. The statistic Q refers to the Ljung-Box test for residual autocorrelation, which in our case follows a χ^2 distribution with approximately 22 degrees of freedom, JB is the Jarque-Bera test for Normality of the residuals having χ^2 distribution with 2 degrees of freedom; SK and Kur are t-test for skewness and kurtosis respectively in the residual series. QS is the modified Pierce test for seasonality of the residuals which is χ^2 with 2 degrees of freedom, Q2 represents the McLeod-Li test of residual linearity (χ^2 with 24 degrees of freedom) and finally, Runs is a t-test for randomness in the algebraic signs of the residuals. Very few of the series failed some of the diagnostics at the 5% level, however, all passed the most relevant Ljung-Box test of residual autocorrelation signifying the success of the differencing transformation in converting the series into stationary stochastic processes.

Table 3

ARMA Parameters of the Noise Models

Percent of Series with AR or MA order	AR(p)	MA(q)	SAR(P)	SMA(Q)
0	50.52%	58.25%	88.66%	56.70%
1	39.18%	38.14%	11.34%	43.30%
2	6.19%	3.09%	0.00%	0.00%
3	4.12%	0.52%	0.00%	0.00%
Total > 0	49.48%	41.75%	11.34%	43.30%
Average of Parameters	0.64	0.46	0.11	0.43

Table 4

Summary of the Diagnostic Tests for the Final Noise Models

Diagnostic Test	Mean Score	Standard Deviation (SD)	Maximum	Minimum	Approx. 1% CV	Beyond 1% CV	% of Series That Pass Test
Ljung-Box LB Test of Residual Autocorrelations	13.30	5.25	28.61	3.74	30.58	0.00	100.00
Jarque-Bera (JB) Test of Normality of Residuals	5.43	12.65	116.42	0.00	9.21	14.95	85.05
Skewness of Residuals t- test	0.06	1.28	4.35	-2.65	2.58	4.12	95.88
Kurtosis of Residuals t-Test	0.79	1.78	10.49	-1.52	2.58	12.37	87.63
Pierce QS test for Residual Seasonality	–	–	6.87	0.00	9.21	0.00	100.00
McLeod and Li Q2 Linearity test	15.40	9.45	61.42	2.85	32.00	4.64	95.36
Runs test for Residual Randomness	-0.17	0.91	2.26	-3.30	2.58	0.52	99.48

SEATS ANALYSIS

After TRAMO generates the pre-adjusted linearized series, SEATS starts the actual signal extraction process. The program produces an output matrix which shows the results of the various procedures employed. The matrix labeled General shows for each series the following information: whether or not the model identified by TRAMO is modified by SEATS; the final model used in the ultimate signal extraction; the standard error of the residuals of the final model; the result of the spectral factorization (i.e., if decomposition of the model has been successful); if the empirical ACF/CCF is in agreement with the theoretical ACF/CCF; and if the signals (trend-cycle, seasonal, irregular and transitory component) estimated by SEATS are modified by some of the deterministic effects captured by TRAMO. The General matrix is the source of the information presented in Table 5 below.

Out of the 194 models pre-adjusted by TRAMO, only 28 (14.43%) are modified by SEATS before the actual signal extraction is undertaken for each series. One reason for the modification is the inadmissibility of the pre-adjusted model for spectral decomposition procedure and this happened to 18 (9.28%) of the models. The other models modified resulted in the fine tuning steps undertaken by SEATS. The quality of the final models used can be gleaned from the proportion of these models in agreement with the theoretical autocorrelation (ACF) and cross-correlation (CCF) patterns. All models (100%) passed the cross-correlation criterion while 97.94% concurred with the autocorrelation patterns predicted by theory.

Table 5

Summary of Regression Outliers and Calendar Variations

Attributes	O U T L I E R S					Calendar Variations		
	Missing Observations (MO)	Additive Outliers (AO)	Transitory Changers (TC)	Level Shifters (LS)	Total	Trading Day (TD)	Easter Effect (EE)	Total
Percent of Series with	0.00%	46.91%	42.27%	53.61%	77.84%	10.82%	4.12%	14.43%
Average Per Series	0	0.77	0.61	0.91	2.29	–	–	–
Maximum Number Per Series	0	5	5	6	14	–	–	–
Minimum Number Per Series	0	0	0	0	0	–	–	–

CONCLUDING REMARKS

Among the most important economic data produced by the Philippine statistical system are the quarterly time series of the components of the country's national accounts. These sub-annual macroeconomic statistics represent an essential input for economic policy-making, business cycle analysis and forecasting. However, these statistics are often swayed by a variety of short term movements which distort one's perception of the true evolution of the variables, thus impeding a clear understanding of the economic phenomena.

The key aspect of handling these mostly unobserved influences is to treat them as important signals that have to be isolated in aid of analysis. Central among these influences is the seasonality (or seasonal fluctuations) of the time series. Statistical agencies worldwide routinely subject most of the sub-annual statistics they produce to seasonal adjustments due to the heavy demand of this treated data from central banks, research institutions and think-tank organizations.

The state of the art in signal extraction gradually evolved from the use of mechanical form of moving average filters to the present sophisticated model-based techniques capable of performing automatic modeling and signal extraction involving hundreds or even thousands of time series in one production run. The leading edge of technology is being shared by two ARIMA model-based systems – ARIMA X12 of the US Bureau of Census and the twin programs TRAMO-SEATS developed at the Bank of Spain. These specialized expert systems have been adopted by most statistical agencies of advanced OECD countries and the European community. The Philippines on the other hand is still using the ARIMA X11 system modified by the Bank of Canada in its routine seasonal adjustment and time series decomposition tasks.

This study is an attempt to implement the ARIMA model-based (AMB) approach of extracting unobserved signals from 194 quarterly national accounts statistics of the Philippines using the TRAMO-SEATS system in a fully automatic modeling mode. The highly successful result of the application adequately demonstrates the feasibility of adopting a system being used routinely by countries in more advanced economies.

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