ABSTRACT
The growing affluence of the East and Southeast Asian economies has come about through a substantial increase in their economic links with the rest of the world, the OECD economies in particular. Econometric studies that try to quantify these links face a severe shortage of high frequency time series data for China and the group of ASEAN4 (Indonesia, Malaysia, Philippines and Thailand). In this exercise we provide quarterly real GDP estimates for these countries derived by applying the Chow-Lin related series technique to annual real GDP series. The quality of the disaggregated series is evaluated through a number of indirect methods. Some potential problems of using readily available univariate disaggregation techniques are also highlighted.

KEY WORDS: Univariate disaggregation, Chow-Lin procedure, first-difference method, growth-rate method, output linkages and forecast performance.
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INTRODUCTION

The fast growing economies of East and Southeast Asia account for a substantial proportion of world trade. They also receive a sizable amount of world FDI. In particular the OECD economies are becoming intertwined with these economics in Asia. Econometric studies that focus on the dynamic relationship between the OECD countries and these Asian economies need quarterly data. Although trade data are available monthly or quarterly, GDP data are mostly available only annually. Unfortunately with annual data most economic relationships become simply contemporaneous because of temporal aggregation. Because of the lack of data many econometric studies use cross-country regressions with untenable underlying assumptions.

If some GDP-related series are available quarterly, they can be used to obtain good estimates of quarterly GDP. Recently we engaged in an extensive study of disaggregating\(^1\) annual GDP of China and the countries in ASEAN4 (Indonesia, Malaysia, Philippines and Thailand) to quarterly figures to be used in a number of macroeconometric models. The objective of this note is to present our methodology and to make the estimated real GDP figures available to other researchers. We also demonstrate why univariate interpolations should be avoided in regressions. The estimation is carried over the period ending in 1996. The Asian financial crisis over 1997-98 distorts the regression estimates.

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\(^1\) Disaggregation is a better term to be used for temporally aggregated or averaged data. It carries a direct meaning. Chow and Lin used “distribution” for this. Interpolation is the term used for stock variables.
METHODOLOGY

The methodology we use stems from Chow and Lin (1971), Fernandez (1981) and Litterman (1983). The basic idea here is to find some GDP-related quarterly series and come up with a predictive equation by running a regression of annual GDP on annual related series. Then use the quarterly figures of the related series to predict the quarterly GDP figures and then adjust them to match the annual aggregates.

The fundamental equation for Chow-Lin disaggregation of \( n \) annual GDP figures to \( 4n \) quarterly figures is

\[
\hat{y} = X\hat{\beta}_a + VC'(CVC')^{-1}\hat{u}_a
\]

(1)

where

\[
\hat{\beta}_a = [X' C'(CVC')^{-1} CX]^{-1} X' C'(CVC')^{-1} y_a,
\]

(2)

\[
C = \begin{bmatrix}
1 & 1 & 1 & 1 & 0 & 0 & 0 & \ldots & 0 \\
0 & 0 & 0 & 1 & 1 & 1 & 1 & \ldots & 0 \\
\ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots \\
0 & \ldots & \ldots & \ldots & \ldots & \ldots & \ldots & 1 & 1 & 1
\end{bmatrix}.
\]

Here \( \hat{y} \) is the \((4n\times1)\) vector of disaggregated quarterly GDP figures, \( y_a \) is the observed \((n\times1)\) vector of annual GDP figures, \( X \) is a \((4n\times k)\) matrix of \( k \) predictor variables, \( V \) is a \((4n\times4n)\) covariance matrix of quarterly error terms \( u_t \), \( \hat{u}_a = y_a - X_a \hat{\beta}_a \) is an \((n\times 1)\) vector of residuals from an annual regression of GDP on predictor variables \( (X_a = CX) \), \( C \) is an \((n\times4n)\) aggregation matrix (or an averaging matrix if multiplied by 0.25) and \( \hat{\beta}_a \) is a \((k\times1)\) vector of GLS estimates of regression coefficients derived from an annual regression.

Chow and Lin presented two forms of \( V \). The simpler one is the case where \( u_t \) is white noise in which case \( V \) is diagonal and the GLS estimator reduces to OLS. In this case the second term on the RHS of (1) amounts to allocating \( 1/4 \)th of the annual
residual to each quarter of the year. The second form is to assume that \( u_t \) follows an AR(1) process of the form \( u_t = \rho u_{t-1} + \varepsilon_t, |\rho| < 1 \) and \( \varepsilon_t \sim iid (0, \sigma^2) \), in which case \( V \) has the well-known form:

\[
V = \sigma^2_v \begin{bmatrix}
1 & \rho & \rho^2 & \cdots & \rho^{4n-1} \\
\rho & 1 & \rho & \cdots & \rho^{4n-2} \\
\vdots & \vdots & \vdots & \ddots & \vdots \\
\rho^{4n-1} & \cdots & 1
\end{bmatrix}.
\]

By extending the monthly-quarterly case considered by Chow and Lin to the quarterly-annual case we get the following equation which can be used to estimate \( \rho \) from the annual estimate \( \hat{\rho}_a \):

\[
(\rho^7 + 2\rho^6 + 3\rho^5 + 4\rho^4 + 3\rho^3 + 2\rho^2 + \rho) \div (2\rho^3 + 4\rho^2 + 6\rho + 4) = \hat{\rho}_a.
\] (3)

A major difficulty with the Chow-Lin procedure, especially in the context of the GDP regressions of this paper, is the possibility of non-stationary residuals. To account for this Fernandez (1981) derived (1) and (2) under the assumption that \( \rho = 1 \). This accommodates a regression based on first differences. As a further generalization Litterman (1983) assumed \( u_t = u_{t-1} + \varepsilon_t \) and \( \varepsilon_t = \rho \varepsilon_{t-1} + e_t, e_t \sim iid (0, \sigma^2_e) \). By setting initial conditions to zero, Litterman derived the expressions in (1) and (2) that involves replacing \( V \) with \( (D'H'HD)^{-1} \) where

\[
D = \begin{bmatrix}
1 & 0 & 0 & \cdots & 0 & 0 \\
-1 & 1 & 0 & \cdots & 0 & 0 \\
0 & -1 & 1 & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & 0 & \cdots & -1 & 1 \\
\end{bmatrix}_{4n \times 4n}, \quad H = \begin{bmatrix}
1 & 0 & 0 & \cdots & 0 & 0 \\
-\rho & 1 & 0 & \cdots & 0 & 0 \\
0 & -\rho & 1 & \cdots & 0 & 0 \\
\vdots & \vdots & \vdots & \ddots & \vdots & \vdots \\
0 & 0 & 0 & \cdots & -\rho & 1 \\
\end{bmatrix}_{4n \times 4n}.
\]
By extending the monthly-quarterly case considered by Litterman to the quarterly-
annual case we get the following equation to derive an estimate of $\rho$ based on $\hat{\rho}_a$:

$$
(\rho^{10} + 4\rho^9 + 10\rho^8 + 20\rho^7 + 31\rho^6 + 40\rho^5 + 44\rho^4 + 40\rho^3 + 32\rho^2 + 24\rho + 10) \div (2\rho^6 + 8\rho^5 + 20\rho^4 + 40\rho^3 + 62\rho^2 + 80\rho + 44) = \hat{\rho}_a
$$

(4)

Note that by setting $H=I$ we revert to the method suggested by Fernandez (1981).

By setting $D=I$ we revert to the Chow-Lin method with AR(1) errors. In this case it is
better to replace the first element of $H$ by $\sqrt{1-\rho^2}$. By setting $D=H=I$ we get the
Chow-Lin method with white noise errors.

Given that many economic time series are well characterized as integrated
processes and integration and cointegration are invariant to temporal aggregation
(Marcellino, 1999) the most recommendable approach to disaggregating a time series
is to find a cointegrating regression and then apply the Chow-Lin technique with a
serial correlation adjustment, if necessary.

If a cointegrating regression is not available then one may have to resort to using
the differenced data series. Unfortunately the first difference method ($\Delta y_t$, as
opposed to $\Delta \ln y_t$), as we call it, does not appear to produce desirable results in every
case. In our attempt to disaggregate the Indonesian and Thai GDP series we tried many
related series, different variants of them (nominal versus real, exports versus total
trade) and disaggregating both nominal GDP and the GDP deflator and then deriving
the real GDP series. We even segmented the sample period in order to get a better
graphical fit for the annual predicted series. Despite all these efforts one problem

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2 Unlike the monthly-quarterly case the polynomial in (3) provides a unique fractional real root for $\rho$
only if $\hat{\rho}_a$ is a positive fraction. The polynomial in (4) provides a unique fractional real root for $\rho$ only
if $\hat{\rho}_a$ is a positive fraction greater than 0.166. For cases that do not fit into these limitations, an
alternative method is required to estimate $\rho$, for example, use available quarterly data.
continued to persist, that is the appearance of a large number of negative quarterly growth rates even during the years when these economies were recording high annual growth rates. To see what was happening we disaggregated Singapore’s GDP series using industrial production index as a related series and compared the quarterly growth rates with the observed ones over the period 1975-1995. Figure 1 plots the results. In the figure the thick line shows the official records and the line with triangles shows the ones based on the first difference method. What we observe is that the first difference method has produced six negative growth rates that do not coincide with official records. One may attribute this to not using a sufficient number of related series, but if a good set of related series are available one may end up with a good cointegrating regression in which case we do not have to resort to the first difference method.³

An alternative solution to the problem is to use the year-on-year (y-o-y) growth rates of the quarterly figures of the related series to disaggregate the annual GDP growth rates and then generate the GDP levels by using the quarterly GDP estimates of a recent year as the base. If \( y_1, \ldots, y_8 \) represent the quarterly GDP figures over two consecutive years and \( Y_1 = y_1 + y_2 + y_3 + y_4 \) and \( Y_2 = y_5 + y_6 + y_7 + y_8 \) are the annual aggregates then the annual growth rate, written against year 2, is

\[
G = 100 \times \frac{Y_2 - Y_1}{Y_1} = w_1 g_1 + w_2 g_2 + w_3 g_3 + w_4 g_4,
\]

where \( g_i = 100 \times \frac{y_{i+4} - y_i}{y_i} \) are the y-o-y growth rates and \( w_i = y_i / Y_1 \) are the weights for \( i = 1, 2, 3, 4 \). If the weights are known then we can apply (1) and (2) to disaggregate the annual growth rates simply by replacing the 1s of \( C \) with the corresponding weights then use four

³ In fact, if the industrial production index is used to disaggregate the manufacturing value added of Singapore we get a strongly cointegrated case and the quarterly growth rates of the disaggregated series track the observed figures beautifully including the seasonal fluctuations.
quarterly figures of a recent year as the base to work out the level of the series. In this case (3) modifies to

\[
(w_1 w_4 \rho^7 + (w_1 w_3 + w_2 w_4) \rho^6 + (w_1 w_2 + w_2 w_3 + w_3 w_4) \rho^5 + (w_1^2 + w_2^2 + w_3^2 + w_4^2) \rho^4 + (w_1 w_2 + w_2 w_3 + w_3 w_4) \rho^3 + (w_1 w_3 + w_2 w_4) \rho^2 + w_1 w_4 \rho + (w_1^2 + w_2^2 + w_3^2 + w_4^2)) = \hat{\beta}_a
\]

(3’)

where the weights are from the first row of the weight matrix.

The growth rate approach has a number of desirable features. First, a regression based on growth rates tends to produce more stable recursive parameter estimates compared to the one based on first differences. Second, it does not require the use of seasonally adjusted data. In fact, it is suitable when the GDP series are highly seasonal. Having to use seasonally adjusted data may induce additional errors. Third, in certain cases, seasonal ARIMA models fit and forecast data series better than the non-seasonal ARIMA models fitted to seasonally adjusted series.

Since the weights are not known a two-step procedure may be followed. Although the weights are not fixed within a year they center around 0.25 year after year. We can, therefore, multiply \( C \) by 0.25 and apply (1) and (2) to derive the first round of quarterly GDP estimates. From these quarterly GDP figures we can estimate the weights. In the Singapore example we observe that the weights computed this way almost coincide with the actual ones. The second step is to use these weights to obtain improved quarterly GDP estimates. In our applications the first and the second steps produce virtually the same GDP growth rates. This is to be expected since the four-quarter average of the year-on-year growth rates is almost the same as the annual growth rate. This is in fact an empirical regularity. Differences occur only at decimal

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4 Note that we have to obtain the annual figures by applying the same aggregation or averaging matrix \( C \) to all the variables regardless whether the RHS variables are flow or stock variables. Otherwise the
places that are practically ignored. Therefore, the second step would be redundant in many cases.

For comparison Figure 1 also plots the quarterly growth rates derived from the growth rate method (the line with circles). It is immediately noticeable that the first difference approach and the growth rate approach produce similar tracks of growth rates but the former introduces much wider fluctuations than the latter. The growth rate approach has produced only one negative quarterly growth rate that does not coincide with the official ones. Moreover, the RMSE of quarterly growth rates from this approach is 25% smaller than that from the first difference approach. For these reasons we use the growth rate approach to disaggregate the China, Indonesia and Thailand GDP series.  

5

Why not univariate disaggregation?

The use of Chow-Lin technique, or the variants of it, is not an easy task because its success depends on the availability of good related data series at higher frequencies. One may wonder, why go through the trouble when there are a number of univariate disaggregation and interpolation methods readily available in a number of computer packages such as SAS. Through our use of such techniques we have encountered a number of undesirable features. One problem we encountered with the parameter estimates at quarterly and annual frequencies will not remain the same. See Wallis (1974) for further insight on the effects of applying different filters.

5 A minor drawback of the growth rate approach is that the quarterly GDP estimates may not add up to the annual estimates due to rounding off errors in growth rates. We observe, however, that the difference between our estimates and official annual figures is very small. Despite this difference annual growth rates of official figures and our estimates remain remarkably close. Since base year changes are going to create discontinuities in the level series it is important to have more accurate growth rates.
univariate techniques in SAS was that they might introduce a pseudo-seasonal pattern into the data series. In general, however, the disaggregated series behaves too smoothly compared to the actual one.

A more serious problem of univariate disaggregation is that the regression relationships may become completely distorted. This distortion is highlighted below through a simple Monte Carlo experiment. The data generating process for the Monte Carlo experiment is the following.

\[ y_t = 10 + 0.6x_t + u_t, \quad u_t = \rho u_{t-1} + \epsilon_t, \]  \hspace{1cm} (5)

\[ x_t = 15 + 0.5x_{t-1} + \eta_t, \]  \hspace{1cm} (6)

where \( \epsilon_t \) and \( \eta_t \) are mutually uncorrelated \( N(0,1) \) variables and \( \rho = 0, 0.3, 0.7 \). By setting the starting values to zero we generated 180 observations and retained the last 80 observations. These observations were then aggregated to form 20 annual aggregates and then the dependent variable \((y)\) was disaggregated using the Chow-Lin technique and three univariate techniques (Spline, Join and Step) available in SAS. The OLS estimation results of model (5) based on 500 replications are given in Table 1.

![Insert Table 1 here]

What is immediately noticeable in Table 1 is that the three univariate techniques produce biased regression estimates whereas the Chow-Lin estimates of \( \alpha \) and \( \beta \) are unbiased. It is not difficult to see why the univariate techniques lead not only to biased but also inconsistent regression estimates. The univariate techniques invariably induce an autocorrelation structure into the disaggregated variable. This is why the
mean estimates of $\rho$ in Table 1 are not zero even when the true $\rho=0$. Furthermore, since the disaggregated values are related to both $x_t$ and $u_t$ in model (5) the errors associated with the disaggregated values become correlated with $x_t$. As a result the OLS estimates become biased and inconsistent. These results highlight a potential danger of using univariate techniques to disaggregate time series.

It is important to note that $\rho$ estimated by solving (3) is biased but consistent. We repeated the Chow-Lin estimator by setting $n=100$ and observed that the mean estimate of $\rho$ approaches the true value as the sample size increases. In Abeysinghe and Lee (1998) it was pointed out that if a sufficient length of quarterly data are available then $\rho$ may be computed directly from the quarterly data. At present, however, there is no satisfactory method to compute $\rho$ in small samples.

**INDIVIDUAL COUNTRY NOTES**

**Malaysia:** Among the disaggregated real GDP series included in this paper the Malaysian series is of the highest quality because of the availability of a rich source of related series. The methodology involved is well demonstrated in Abeysinghe and Lee (1998). In this case since the disaggregation was done based on regressions for three major sectors (industry, agriculture and service) that guaranteed stationary residuals what required was the direct use of the Chow-Lin formulas in (1) and (2). The disaggregated series which is seasonal closely tracks the official series during the overlapping period.

It should be noted that the quarterly figures for recent years are not available in a systematic manner. The IFS CDROM quarterly data series ends in 1995Q4. Therefore, data updating has to be done mostly on the basis of published GDP growth rates from sources like the Quarterly Bulletin of Bank Negara Malaysia.
**Philippines:** For the Philippines we did not resort to using related series because half yearly data were available from 1975 to 1980 and quarterly figures from 1981Q1 onwards (IFS CDROM). The half yearly figures are reported at the end of the second and fourth quarters. To estimate quarterly real GDP for the period 1975 to 1980 we used an ARIMA forecasting technique. For this, we put the data series 1981Q1-1996Q4 in reverse order (1996Q4-1981Q1) and fitted the ARIMA model $\Delta \Delta \ln(GDP_t) = -0.3\Delta \Delta \ln(GDP_{t-1}) + e_t$ and generated a one-step ahead forecast to estimate 1980Q4 value, then subtracted this figure from the reported 1980 second half figure to obtain the 1980Q3 figure. Then using these values we obtained another one-step forecast as an estimate of 1980Q2 figure and 1980Q1 was obtained by subtraction as above. Proceeding this way provided quarterly GDP estimates, which add up to the annual totals and retains the seasonal component.

**Thailand:** For China, Indonesia and Thailand we used the growth rate approach discussed in Section 2. We start with Thailand because the methodology we use for Thailand has a general applicability. However, as we experienced with Indonesia, the success is not always guaranteed. The basic methodology is to disaggregate the nominal GDP series and then deflate it to derive the real values. The most commonly available good-quality GDP-related series are exports, imports and M1 money stock. A regression of nominal GDP on the nominal quantities of these variables is likely to perform much better than a regression of real (deflated) variables. If the GDP deflator forms a tight relationship with CPI then the deflator can also be disaggregated and then use for deflating nominal GDP. If this does not work well the alternative is to use
CPI to obtain a nominal GDP series and then use CPI again to deflate the 
disaggregated series. In the case of Thailand the latter approach works better.

Since 1998 the National Economic and Social Development Board of Thailand 
(www.nesdb.go.th) has begun to compile quarterly GDP figures by sector. These 
figures go back to 1993Q1. The same website provides annual GDP figures, both 
nominal and real (at 1988 prices), starting with 1951. The related series were obtained 
from the IFS CDROM and local sources (mainly the Quarterly Bulletin of Bank of 
Thailand). We were first trying to disaggregate the real GDP growth rates. The key 
variables that turned out to be useful in this regression were the nominal total external 
trade and the nominal M1 money stock. But these variables alone are not sufficient to 
account for a substantial jump in growth rates after 1986. Although FDI inflow 
available quarterly since 1976) can account for this jump, the real GDP series 
disaggregated in this way exhibits a troublesome autocorrelation structure. When we 
switch to nominal GDP, however, both M1 and FDI become highly insignificant. 
Therefore, the final GLS regression that we used, based on growth rates of nominal 
variables, is

\[ GDP = 8.62 + 0.29 \text{Trade} \]

\[ (5.78) \quad (5.33) \]

\[ R^2 = 0.63, \quad \hat{\rho}_n = 0.36, \quad \hat{\rho} = 0.66. \]

where the numbers in parenthesis below the equation are the t-ratios and the sample 
period is 1971-1996. The recursive parameter estimates of this regression are highly 
stable. The annual growth rates from the estimated quarterly real GDP figures are 
virtually the same as the observed ones.
Indonesia: For Indonesia quarterly real GDP (1993 base) is available from 1989Q1 onwards from Economic Indicators, Monthly Statistical Bulletin, Indonesia. The Bank of Indonesia website reports quarterly nominal GDP from 1990 and real GDP from 1997 onwards. The annual GDP series from different international sources are not very consistent. The annual series that we use were supplied to us by BPS-Statistics Indonesia (Badan Pusat Statistik). Although quarterly data on exports, imports and M1 money stock are available since 1971 (IFS CDROM), data on two other important variables, mining and manufacturing output indices are available only since 1978 (Statistical Indicators for Asia and Pacific, ESCAP, UN). In order to produce a consistent series from 1971 onwards we tried to follow the same approach that we used for Thailand. Although nominal GDP regressions fit the data very well the deflated series (based on both disaggregated GDP deflator and CPI) produce highly unreliable GDP growth rates. Both the first difference and growth rate approaches lead to the same problem. Therefore, we produce quarterly GDP series only from 1978 onwards.

The regression that we use based on the growth rates of real GDP, mining and manufacturing output indices and nominal M1 over 1979-1996 is:

\[
\text{GDP} = 3.89 + 0.17 \text{Mining} + 0.14 \text{Manuf.} + 0.06 \text{M1}
\]

\[
\begin{align*}
& (5.68) & (3.17) & (2.09) & (2.04) \\
\end{align*}
\]

\[R^2 = 0.71, \hat{\rho}_n = 0.24, \hat{\rho} = 0.53.\]

Although the recursive parameter estimates of this regression are very stable the predicted values track the observed growth rates well only until 1987. Fortunately the official quarterly figures start from 1989.

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\[\]

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\[\]

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6 In fact, the Thai case consumed a substantial amount of our time and energy because we were pre-occupied with disaggregating the real GDP series.
China: In the case of China quarterly nominal GDP in levels and real GDP in growth rates are available from local sources since 1995Q1. Our sources of quarterly data are The People’s Bank of China Quarterly Statistical Bulletin and Chinese Economic Trends. The latter is a quarterly publication of the Beijing CETA Institute of Economics. In these publications quarterly nominal GDP is reported on a cumulative basis. These are then converted to real GDP growth rates. Real GDP levels and the price deflator are not available. Deflating nominal GDP by published price indexes such as CPI or RPI (retail price index) does not produce the published real GDP growth rates. We, therefore, first converted both nominal GDP levels and real GDP growth rates into quarterly figures and then used 1997 as the base year to construct our quarterly real GDP series. We choose 1997 as the base because growth rates of nominal and real GDP for 1997 are roughly the same. Using these nominal and real GDP series one can derive the GDP deflator implicit in the published real GDP growth rates.

For China, annual GDP figures consistent with the United Nations System of National Accounts are available only since 1978 (China Statistical Yearbook). There are, however, serious concerns about the accuracy and veracity of these numbers especially since the mid-1990s. Rawski (2001), for example, argues that GDP growth figures since 1998 are highly exaggerated and unreliable. According to Wang and Meng’s (2001) calculations the overestimation of growth figures has been present even in the earlier periods largely due to insufficient deflation of nominal figures. They argue, however, that large exaggerations have begun to occur since 1992. Zheng (2001), on the other hand, defends the quality of the official statistics. ⁷ For this exercise, we use the official GDP figures and as we shall see in Section 4 despite the
alleged shortcomings of the GDP figures they capture the international linkages reasonably well.

For the disaggregation we use the following growth regression of real GDP on nominal M1 and nominal total external trade based on the sample period 1979-1997:

\[
GDP = 5.42 + 0.07M1 + 0.21\text{Trade} \\
(3.49) (1.02) (3.72)
\]

\[R^2 = 0.66, \hat{\rho}_a = 0.28, \hat{\rho} = 0.58.\]

The recursive parameter estimates of this regression are reasonably stable. We retain M1 in the regression, though statistically insignificant, because it leads to better disaggregated growth rates during the overlapping period. Interestingly both the first-difference approach and the growth-rate approach produce virtually the same growth rates for China. The \(R^2\) value of 0.66 for a growth regression of real GDP on nominal variables is quite impressive. This perhaps supports Wang and Meng’s argument of insufficient deflation.

**QUALITY OF THE DISAGGREGATED SERIES**

Figure 2 provides a graphical presentation of the disaggregated series appended with the official figures. All series are strongly seasonal and the logarithmic transformation produces a more stable seasonal pattern. The main exception is the Philippines series, which contains a very stubborn seasonal pattern that seems to have resulted from the variations in the data compilation methods.

\[\text{Insert Figure 2}\]

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\^7 See also a number of other papers in China Economic Review, 12(4), 2001, that address the quality of China’s statistics.
A direct measure of the quality of the disaggregated GDP series is the RMSE of y-o-y growth rates computed against the observed ones over the overlapping periods. For China the RMSE over 1995-1997 is 1.4% which is not unreasonable against a 10% average growth rate over this period. For Indonesia the RMSE over 1990-1996 is 1.1%. This is also an impressive number when judged against a 7% average growth rate over this period and the poor graphical fit of the annual regression after 1987. For Thailand the RMSE over 1994-1996 is 1.7%. The average growth over the same period was 8%. Compared to China and Indonesia the accuracy of the Thai figures appears to be low.

An indirect way to assess the quality of these series is through model fitting and forecast evaluations. A good fit and, therefore, good forecasts are unlikely if the disaggregated series contain substantial errors. In this section we summarize results from three types of models, ARIMA and two VAR models.

After a standard search procedure we fitted the following ARIMA models to $y_t = \ln(GDP)$. We use these models in the out-of-sample forecast evaluation given in Table 3. The Q statistic reported below each equation is the LJung-Box Q statistic to test for the presence of residual autocorrelation based on 24 autocorrelations. The conclusion of the Q test is the same even if a different number of autocorrelations are used. The numbers in parentheses below the coefficients are t-ratios.

**China (1978Q1-1993Q4):**

$$\Delta y_t = (1 - 0.24 L) e_t, \quad \hat{\sigma}_e = 0.018, \quad Q(23) = 16.08 \text{ with } p-value = 0.852.$$  

(10)

**Indonesia (1978Q1-1993Q4):**
\[ \Delta \Delta_t y_t = (1 - 0.65 L^4) \epsilon_t, \quad \sigma_\epsilon = 0.014, \quad Q(23) = 9.86 \text{ with } p-value = 0.992. \] (4.46)

Malaysia (1975Q1-1993Q1):

\[ \Delta \Delta_t y_t = (1 - 0.51 L^4) \epsilon_t, \quad \sigma_\epsilon = 0.018, \quad Q(23) = 15.15 \text{ with } p-value = 0.889. \] (4.62)

Philippines (1975Q1-1993Q4):

\[ \Delta \Delta_t y_t = (1 - 0.35 L^4) \epsilon_t, \quad \sigma_\epsilon = 0.029, \quad Q(23) = 27.95 \text{ with } p-value = 0.218. \] (3.15)

Thailand (1970Q1-1993Q4):

\[ \Delta \Delta_t y_t = (1 - 0.24 L)(1 - 0.75 L^4) \epsilon_t, \quad \sigma_\epsilon = 0.02, \quad Q(22) = 13.90 \text{ with } p-value = 0.905. \] (2.36) (9.13)

The selected ARIMA models fit the data very well and the models are well in line with the Box-Jenkins seasonal ARIMA structure. We observe that seasonal dummies are not appropriate to model the seasonality in these series despite the propagation of the base-year seasonal pattern to the disaggregation period. If seasonal dummies are appropriate seasonal differencing should produce seasonal MA unit roots, which is not the case with the above models.

Next we consider how well these series pick up their linkages with the major trading partners. For this we adopt the framework developed in Abeysinghe (2001) and Abeysinghe and Forbes (2001). A priori we expect statistically significant output linkages to exist among the major trading partners. Let \( y_{it} = \ln(GDP_{it}) \) and \( y'_{it} = \ln(Y'_{it}f) \), where the subscript \( i \) represents the \( i \)th country and \( Y'_{it}f \) is the export weighted GDP of the major trading partners of the \( i \)th country. To compute \( Y'_{it}f \) we
use eleven countries and one region, the five countries studied in the paper, NIE4 (Hong Kong, Singapore South Korea, Taiwan), Japan, USA and the rest of OECD as a group. Thus $Y^f_i$ is the average GDP of eleven economies excluding the one represented by $i$. The export shares are 12-quarter moving averages so that the trade pattern is allowed change slowly over time and $Y^f_i$ is a geometrically weighted average.\(^8\) To study the output linkages we use the model

$$
\Delta y_{it} = \sum_{j=1}^{4} \phi_j \Delta y_{i,-j} + \sum_{j=0}^{4} \beta_j \Delta y^f_{it-j} + \epsilon_{it} 
$$

(15)

where $\epsilon_{it}$ is assumed to be a white noise process with zero mean and constant variance. From (15) we can compute the long run output elasticity for the $i$th country as

$$
\beta_i = \frac{\sum_{j=0}^{4} \beta_j}{(1 - \sum_{j=1}^{4} \phi_j)}.
$$

(16)

We estimated model (15) using seasonally adjusted data (based on X11) over the period 1978Q1-1993Q4. The long run output elasticity estimates ($\beta_i$) and a number of model diagnostics provided by PCGIVE (Hendry and Doornik, 1996) are reported in Table 2.

Concurring with apriori expectations, the long run output elasticity estimates in Table 2 are highly significant (indicated by the Wald test) except for the Philippines. A 1% increase in the GDP growth of the major trading partners can produce more than 1% GDP growth in these countries in the long run. The statistical insignificance

\(^8\) The geometric average is a property of the model developed in Abeysinghe and Forbes (2001).
of the Philippines estimate may be a data problem or a genuine effect that represents the long stagnation of the Philippines economy compared to the trading partners. The model diagnostics are impressive and the residuals in general satisfy the standard regression assumptions. The noteworthy exception is that Thailand fails the Chow test. We have to note that the Thai economy started to falter since late 1996, though the neighboring trading partners were doing well, and paved the way for the Asian financial crisis. If we exclude 1996Q4 from the forecasting period, the Chow test clears through.

As shown in Abeysinghe and Forbes (2001) equation (15) has a hidden VAR structure that can be exploited for forecasting purposes. The VAR model has the form

\[
(B_0 * W_t) \Delta y_t = (B_1 * W_{t-1}) \Delta y_{t-1} + \ldots + (B_4 * W_{t-4}) \Delta y_{t-4} + \varepsilon_t
\]  

(17)

where \( y_t \) is an \((n \times 1)\) vector of log GDP series, \( B_j \) (\( j=0,1,\ldots,4 \)) are \((n \times n)\) restricted parameter matrices and \( W_t \) is an \((n \times n)\) matrix of weights computed from bilateral export shares.\(^9\) The asterisk indicates the Hadamard (element wise) product. In this model \((B_j * W_{t-j})\) constitute the effective parameter matrices. (See the above references for more details.) We refer to model (17) as a structural VAR model. The growth forecasts based on a model like (17) are likely to be highly inaccurate if international linkages are distorted by the disaggregation process. For comparison we also fit a standard unrestricted VAR(4) model to the twelve GDP series and generated forecasts.

We estimated the models using data up to 1993Q4 and forecasts were computed over the period 1994Q1-1996Q4. Since forecast failures are well
highlighted in growth rates we computed the RMSEs of year-on-year growth forecasts. Table 3 presents the RMSEs of the structural VAR and standard VAR models relative to that of ARIMA models for the disaggregated series. What is immediately noticeable from Table 3 is that the standard VAR model forecasts worse than the ARIMA models. The only exception is the 1-step forecasts for Thailand. On the other hand the structural VAR performs better than the ARIMA models except for the Philippines at the 3rd and 4th steps. Standard unrestricted VAR models are known to produce poor forecasts and we juxtaposed the results for both VARs to highlight that the poor forecasting of standard VAR is not due to the disaggregation quality of the series. The improved forecasting performance of the structural VAR model confirms that the disaggregation process has not distorted the international linkages.

===================
Insert Table 3 here
===================

CONCLUSION

In the disaggregation process we paid careful attention to the movements of quarter-on-quarter and year-on-year growth rates, the autocorrelation structure of the generated series and how the generated series capture important international linkages. Despite the data constraints, the disaggregated series appear to be of good quality. Even the RMSEs of growth rates during overlapping periods, a broad measure that hides important details, are reasonably low compared to the average growth rates experienced by these economies. This exercise taught us that disaggregating a GDP

---

9 For n=12 countries each with 11 trading partners we need 132 bilateral export series to perform the above computation. These data are from The Direction of Trade Statistics, various issues.
series may not be as straightforward as a theory suggests especially when high-quality related series are not available.

The table in the Appendix reports year-on-year growth rates of the disaggregated real GDP series extended by the official figures that are published either in IFS CDROM or local sources cited above. These growth figures can easily be converted to real GDP levels by using quarterly GDP figures of a recent year and working backward. It is advisable to use a recent year to start the backtracking because the recent real GDP figures may have started with a new base. The complete data set, the real GDP levels and the related series, can be downloaded from the URL: http://courses.nus.edu.sg/course/ecstabey/gdpdata.xls or from http://www.fas.nus.edu.sg/ecs/center/esu/index.htm.

REFERENCES


Appendix

Real GDP growth rates
Percentage change over the same quarter of previous year

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Table 1. Mean OLS estimates based on Chow-Lin and univariate disaggregation techniques, 500 replications, n=20, 4n=80

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<td>18.22</td>
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<td>Malaysia</td>
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<td>41.46*</td>
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The numbers in parentheses are p-values. * indicates the rejection of the null hypothesis at the 5% level. Both Wald test and Normality test are chi-square tests and the rest are F tests. The estimation period is 1978Q1 – 1993Q4. The Chow test is over the 12 quarters from 1994Q1 to 1996Q4.
Table 3. RMSEs of year-on-year growth (%) forecasts

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<td>2.66</td>
</tr>
</tbody>
</table>

Note: RMSEs for VAR models are given as ratios against ARIMA models. Forecast period is 1994Q1-1996Q4.
Figure 1. Singapore’s quarterly GDP growth rates (%): Solid line = observed; triangle line = first-difference based; circle line = growth-rate based.
Figure 2. Real GDP series in logarithmic scale