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A New Look at China's Output Fluctuations: Quarterly GDP Estimation with an Unobserved Components Approach

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Abstract

This paper provides quarterly real GDP estimates for China from 1978q1-1991q4 using an unobserved component approach. The approach imposes fewer prior restrictions on related series and is more flexible than other disaggregation methods. The multivariate unobserved components model with total trade and domestic credit as related series is selected as the best fit model for temporal disaggregation of China's real GDP. The estimated quarterly real GDP data are then evaluated with univariate and multivariate time series analysis techniques. The constructed quarterly data are shown of good quality and provide valuable information for the analyses of China's macroeconomic fluctuations during the period.

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I. Introduction

"China moves to centre stage"

----Cover story, *Economist*, Oct. 30, 2008

In the past three decades, China has emerged as one of the most important and influential economies, with its remarkably rapid growth and integration into the world economy. China is the world's second largest economy in 2010[2], the largest exporter (since 2009) and the world's largest foreign exchange reserves holder. The recent financial crisis pushed China to the frontier of world economic development. China's economic performance, in the short and long run, is more than ever the focus not only of academic research but also of policy makers and stakeholders from inside and outside China.

Although increasingly important, the properties of China's output fluctuations are not well understood. Very limited econometric analysis has been conducted on China's macroeconomic fluctuations. This is mainly due to the shortage of high-frequency data. The complexity of China's transitional economic and political structures adds difficulties to the analysis. Lack of proper characterization of China's output trend and cycles may mislead the theoretical economic studies on Chinese economy as well as policy analysis. While existing research relies mostly on the available annual data, the study from low-frequency annual data obviously cannot fulfill the needs of economic decision making in a fast-changing world.

China's official quarterly real GDP data are only available since 1992, which provides only 78 quarterly observations up to 2011 q2. Small samples can limit the applicable methods and the quality of empirical analysis. Just shortening the sample period and ignoring the

[2] China passed Japan as the second largest economy in terms of nominal GDP in 2010.

available annual observations before the quarterly data are available results in losing important information for the properties of data generating process. Extending the quarterly real GDP data from 1992 back to 1978 for China would provide a complete sample of growth fluctuations for the economy since the beginning of the reforms and thus a better understanding of the evolving properties of China's macroeconomic fluctuations along with the implementation of the reforms.

As to flow data such as real GDP, one way to solve the above problem is to temporally disaggregate or interpolate the low frequency data into higher frequency data. Using a proxy observed at higher frequency and estimating the real GDP with the production function would be alternatives. However, for China, quarterly macro-economic data before 1992 are extremely limited. The only available series are from monetary and international trade statistics. They are not sufficient to estimate the proxy and production function data construction alternatives. Temporal disaggregation of annual real GDP to quarterly real GDP with available related information thus becomes the only practical approach for the quarterly GDP construction for the period. Temporal disaggregation is also a commonly used method for resolving similar problems to other countries[3]. Univariate methods, related series univariate method or Chow-Lin method (Chow and Lin 1971, CL model hereafter) and multivariate unobserved components (UC approach hereafter) methods are the three groups of approaches that have been applied to temporal disaggregate macro-economic data in literature.

Abeysinghe and Rajaguru (2004, A&R hereafter), the only published study on the temporal disaggregation of China's GDP data, applies the Chow-Lin related series technique to disaggregate China's annual real GDP data into quarterly data and provides quarterly real GDP

[3] For example the Eurostat (1999) documents that the temporal disaggregation method is used in the official statistics agencies of the European countries.

growth rate estimates from 1978Q1 to 1994 Q4[4]. However, as I will discuss below, the CL model based on univariate regression assumes a linear relationship among the related series and does not consider the unit root properties of the series. Both assumptions may not be proper in practice when choices of available related series are very limited.

My study generalizes the univariate and multivariate unobserved components modeling for temporal disaggregation, and provides temporal disaggregate estimates of China's quarterly real GDP data for the years 1978 through 1991 using the selected multivariate unobserved components model (MUC model hereafter). The unobserved components approach is more general than the Chow-Lin approach in dealing with unit root, seasonality and irregularity properties. The method allows simultaneous disaggregation and seasonal adjustment of the data, and imposes minimum prior restrictions on the data. It provides more flexibility for the data selection, which is especially important for emerging countries whose high frequency data are very limited.

I temporally disaggregate China's real GDP series using the unobserved components models with different specifications of components and different combinations of related series for model selection. The multivariate unobserved components (MUC) model with domestic credit and total trades as related series is selected as the best fit model based on the root mean squared standard errors of the estimated data and the official published data over the overlapping

[4]On their website (http://courses.nus.edu.sg/course/ecstabey/gdpdata.xls), the authors extended the series through 2007Q1, using quarterly year-on-year real GDP growth rates from the country data of Economist Intelligence Unit. The data resources of EIU country data for China are CEIC and National Bureau of Statistics of China (NBS).

period. The estimated data from 1978-1991 with selected MUC model are more efficient than the estimation from other temporal disaggregation methods[5].

The MUC estimated quarterly real GDP for China provides a better alternative of China's quarterly real output data for different univariate and multivariate time series analyses. To evaluate the data quality, I apply different univariate trend cycle analyses, such as Hodrick-Prescott filter (1997, HP filter hereafter), Band-Pass Baxer-King (1999) and Christiano-Fizgerald (2003) filter and unobserved components decomposition method, and structural multivariate analysis, such as Blanchard-Quah (1989) decomposition and Global Vector Autoregression models (Dees et. al 2007, DdPS model hereafter) to the estimated data. The analyses show that the extension of quarterly real GDP with the MUC model provides valuable information for the understanding of the output fluctuations during the sample period. Domestic factors and supply shocks are found to be the main driver of China's output fluctuations.

The purpose of this paper is to provide quarterly real GDP for China in consistency with the official real output data. Thus, the availability and reliability of China's official data, the big concerns for China's official GDP statistics, are carefully discussed before the data construction.

There are six sections of this paper: Section II reviews the relevant literature on the methodology of temporal disaggregation and the contribution of my paper in high frequency data construction; Section III presents the unobserved components or structural time series models for the temporal disaggregation of China's real GDP. Section IV addresses China's macroeconomic data problem. In Section V, the results of the data construction from different model specifications are presented and evaluated. Section VI analyzes China's real GDP fluctuations

[5]The comparison of the estimation of different approaches based on the root mean square errors is presented in section V. The selected MUC estimation, including the observed annual levels in the estimation, fits the observed annual real growth rates better than the A&R estimation.

with the constructed quarterly real GDP data using different univariate and multivariate approaches and compares the results of permanent and transitory macroeconomic fluctuations based on the constructed quarterly real GDP data. Section VII concludes.

II. The literature

This study is related to the following strands of literature: first, the estimation of missing high-frequency macro economic data from available low-frequency data, i.e. interpolation and temporal disaggregation methods; second, the research on identifying China's output fluctuations and the commonly used univariate and multivariate aggregate output trend and cycle decomposition methods. To evaluate the quality of the quarterly real GDP data estimated in this paper, both univariate and multivariate methods are applied to the estimated quarterly real GDP data for China. The unobserved components model is the key modeling framework applied in this paper.

2.1 Literature on missing high frequency data and temporal disaggregation methods of time series

Temporal disaggregation or interpolation has been extensively used by researchers when high frequency data required by econometric analysis are not available. It is also a routine practice for official statistical agencies to apply temporal disaggregation methods to generate high frequency data, especially when direct estimation methods are unavailable or information collection is costly (Proietti 2006, Eurostat, 1999).

Problems of time series disaggregation include interpolation of stock variables and temporal disaggregation of flow variables. The estimation of China's quarterly Gross Domestic Product from the annual official data falls into the second category. There are broadly three groups of methods that have been developed to temporally disaggregate lower frequency data into higher frequency data:

1) univariate methods rely on the time series properties of the targeted series only. For example, Stram and Wei (1986, 1990) derive smoothed estimation of unavailable high frequency data based on the ARIMA structure of the series. Stram and Wei (1990) method has been applied to the estimation of macroeconomic indicators by many official statistic agencies (Eurostat 1999, part 6.45-6.46).

When the missing high frequency data period is short compared to the whole sample period, a simple univariate interpolation is often convenient. However, when missing high frequency data are for a relatively long period, the simple univariate interpolation, which uses the time series properties of the target series itself (usually properties of the series during more recent period when the high frequency data are available), is likely to distort the results of high frequency analysis. Especially for the sample period when high frequency data are missing. The problem may be more serious for data from emerging or transitional economies. Their underlying economic structure and environment often change substantially. More sophisticated methods that use more information to disaggregate data should be considered.

2) Related series univariate models that were first proposed by Chow and Lin 1971 and extended by Fernandez (1981) and Litterman (1983) with a random walk and I (1) error term respectively. Application of temporal disaggregation by the CL approach begins with running OLS or GLS on a linear model of target series to the related series with low frequency data. Assuming that the linear relationship of target series and related series is consistent with low frequency and high frequency data, the estimated coefficients are then used to predict the target series based on the high frequency related series data with adjustment to match the annual

aggregates. An AR (1) process for the error term is assumed in the original CL model. To account for the non-stationary residuals, a random walk process is assumed in the Fernandez model and I (1) in the Litterman model. Santos and Cardoso (2001) and recently Proietti (2006) add lagged values of the dependent variable (autoregressive distributed lag or ADL models) into the CL model. Harvey and Pierse (1984) and Proietti (2006) present these groups of models in state space form and apply the Kalman filter to estimate the missing observations.

The CL approach and its extension models use more information from observed related high frequency data. Chen (1993) demonstrates with Monte Carlo simulated data that the CL procedure is usually more efficient than the univariate only alternatives. The convenience in application has made this method more popular in practice than the first group of models. A&R (2004), the only published temporal disaggregation of China's real GDP, applies CL approach to the growth rates of GDP with the growth rates of M1 and total trade as related series.

The major problem with this group of models is that the assumption of a linear relationship between the target series and the related series is often difficult to verify with the data (Proietti 2006, Moauro and Savio 2005).

As Harvey (1989 section 8.7) and Proietti (2006) mentioned, the univariate related series models, although widely applied in practice, impose a strong assumption of cointegrating relationship between targeted series and the related series and/or exogeneity of the related series regressors. Moauro and Savio (2005) further proves that even with the existence of cointegrating relationship, univariate with related series models, or CL method will be efficient only when the constant and the autoregressive parameters are equal for all included related series, or in terms of unobserved component model specification, the related series are trend homogeneous. The assumptions are not likely to be verified in the true data, especially when the choices of related series are very limited[6].

The restriction of CL methods limits the choice of related series. The target series and the sets of available "related" series may not have a linear relationship, but are usually affected by the same economic environment and thus could provide valuable information and improve the efficiency of the disaggregation. A&R, who use nominal M1 and the total trade as related series, apply CL approach to the first-differences and the growth rates instead of levels of the real GDP and related series to avoid the non-stationary and cointegration problem. Even with the growth-rate approach, A&R did not find a significant linear relationship between the growth rate of real GDP and M1, but found including M1 leads to better disaggregation[7]. Although the relationship of M1 and real GDP is not significant with annual data, it provides information for quarterly GDP estimation that improves the efficiency of the disaggregation.

3) Multivariate unobserved components (MUC) or structural time series models. The application of UC models to temporal disaggregation was originated by Harvey and Pierse (1984) and Harvey (1989)[8]. Harvey and Chung (2000), Moauro and Savio (2005) are examples of the contributions of this group of models. MUC models set up a system of unobserved components equations of the targeted and related series and estimate the models in the system simultaneously. The approach allows cross series correlations for the components and thus includes the quarterly information provided by the available related series to the disaggregation of target series.

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[6] When choices of related series are limited, if no linear relationship is found among the series, there will be no alternatives available.

[7] A&R evaluates the disaggregation by comparing the quarterly data estimated from the model with the real data during the overlapping period.

[8] Harvey (1989) names his model "seemingly unrelated structural time series equation (SUTSE)".

The MUC approach overcomes the limitation of CL methods. The MUC models are capable of taking advantage of information from the available high frequency “related” time series for the disaggregation, without putting prior restrictions on the specific relationship between the series. Common trends, common cycles and common seasonalities among the related series can be tested through MUC models (Moauro and Savio 2005). The MUC approach is also flexible in handling both seasonally adjusted and non-seasonally adjusted data and allows disaggregation and seasonal adjustment simultaneously. Proietti and Moauro (2005) further show that the model is capable of handing seasonality very well. In addition, with the Kalman smoothing estimation, the sample period can be extended to include the information of the available high frequency observations of the targeted series in the later years. For example, China’s official quarterly real GDP data that are available since 1992 can be included in the estimation of China’s real quarterly GDP during 1978-1991 in MUC models. Since the time series property of a time series itself is usually stable over time, the property of the observed high frequency data of the target series can help improving the temporal disaggregation.

Since Harvey and Pierse (1984) first cast the univariate disaggregation methods into state-space form and applied Kalman filter technique to estimate the missing high frequency data, the state space approach has been regularly applied in the temporal disaggregation of time series. Harvey (1989, section 6.3) proposed the method of using cumulator series to set up the state space form over series of different time frequencies, where the missing high frequency data is treated as missing observations, estimated with the Kalman smoothing algorithm. The method provides more flexibility in modeling components of the series and can be applied to both univariate and multivariate disaggregation models on both flow and stock time series. Durbin and Quenneville (1997), Proietti (2006) generalized the state space method applications to the

CL model and its extensions. The related series are modeled as exogenous regressors that enter into the measurement equation and/or transitory equation. Cuche and Hess (1999) and Tasdemir (2008) disaggregate European and Turkish data using the state space methods.

This paper further generalizes the models for the temporal disaggregation of flow series with unobserved components stemming from Harvey (1989) and Moauro and Savio (2005). I present the univariate and multivariate unobserved components models, with or without cyclical components, in state space forms and estimate China's quarterly real GDP during 1978-1991 with Kalman smoothing algorithm. This paper is the first application of temporal disaggregation of China's real GDP with the unobserved components approach.

2.2 Literature on identifying and characterizing China's output fluctuations

To evaluate the information provided by the quarterly real GDP levels of China from 1978-1991 estimated by the selected unobserved components model in this paper, I apply different univariate and multivariate time series analytic methods to the data. Literature on the measurement of China's potential output or output gap is then closely related to this part of study. The existing studies generally follow three approaches: the production function approach, univariate trend-cycle decomposition approaches and multivariate time series approaches or Vector autoregression approaches (VAR).

The trend of aggregate output is generally assumed to correspond to potential output and the cycle is assumed to correspond to the output gap. Most of the studies on China's potential output estimation apply production function approach to annual data, which estimates the Cobb-Douglas production function with potential capital and labor inputs[9].

[9] In this group of studies, Chow (1993 and 2002) intends to find the importance of capital formation and contributions of sectors, Heytens and Zebregs (2003) try to find the growth of Total Factor Productivity, Young (2003) focuses on alternative

Decomposition of the aggregate output series into trend and cycle components has been a common practice for aggregate output fluctuation analysis. Competing approaches have been developed to decompose macroeconomic series such as the aggregate output into "trend" and "cycle", or permanent and transitory components. A number of studies (Morley 2008, Canova 1998, Zarnowitz and Ozyildrim 2006, Park 1996 and King and Rebelo 1993, Gerlach and Yiu 2003) have shown that the revealed trend cycle properties are sensitive to the detrending methods[10].

For China's real GDP, the Hodrick-Prescott (HP) filter is the widely used univariate detrending method in the literature that models China's business cycles (for example: Ha, Fan and Shu 2003)[11]. Gerlach and Peng (2006) estimate annual Chinese output gap from 1982-2003 using the unobserved components (UC) model following Watson (1986) and Clark (1987). They find that HP filter and UC approaches generate similar cyclical patterns. Their estimation suffers from limitations due to the small sample size (21 observations) and very broad confidence bands. Laurenceson and Rodgers (2010) use different frequencies of cycles to identify the relative importance of demand and supply volatilities occurring at China's business cycle.

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price levels, and Scheibe and Vine (2005) study the Phillips curve. Scheibe (2003) explores the production function with sector based estimation. This approach is also used for alternative GDP data constructions.

[10] Canova (1998) examines the business cycle properties of US real macroeconomic time series data with seven different decomposition methods and finds that for aggregate output of the US, different decomposition methods generate cycles that differ in time duration and turning points. As for developing countries, Gerlach and Yiu (2003) compare output gaps with annual data for eight Asian economies (not including China) derived from four decomposition methods, and find gaps (cycle component) from HP, UC and BP decompositions are similar for these countries but the gaps derived by BN decompositions are different.

[11] Although the production function approach uses more information for potential GDP estimation than the alternative univariate approaches, it also introduces more potential problems. First, several assumptions are frequently made to set up the production function. Assumptions such as constant returns to scale in production, competitive markets for inputs and outputs may not be appropriate for China. There are no generally accepted potential levels of labor, capital inputs and total factor productivity growth for China. Secondly, the estimation needs capital and labor data, which faces similar data availability and reliability problems as well. Labor or employment data are even less available and reliable for China than GDP data. Missing capital and employment data have to be estimated before they are used in the potential GDP estimation. Third, the estimation must select proper price levels for different inputs and sectors (Young 2003), which are unavailable and have to be estimated. Finally, most research using this approach relies only on annual data due to the data availability problem. Because of the issues above, the results of production function estimations are not consistent among different studies.

In recent years, several Chinese scholars applied nonlinear univariate methods such as Markov-switching process to indentify the phases of business cycles in China (mostly published in Chinese), examples of the studies include Chen and Liu (2007) Liu (2003, Liu and Zheng (2008), Zheng, Teng and Song (2010). Most of these researches suffer from small sample problem.

In this paper, I apply the most widely used univariate methods include the Hodrick and Prescott (1997, HP) filter, the Band-Pass filter (Baxter and King 1987, Christiano and Fizgerald 2003, BP) filter, and the unobserved components models (Harvey 1985, Watson 1986, Clark 1987) to the estimated quarterly real GDP data to present the information provided by the data.

Structural multivariate methods, on the basis of economic theories, introduce other macroeconomic variables to identify the properties or the origins of output fluctuations. These methods include the structural VAR, such as Blanchard-Quah (1989) approach and its extensions (e.g. Clarida and Gali 1994) and multivariate system models such as the global VAR approaches (Dees, Di Mauro, Pesaran and Smith 2007, DdPS hereafter). The current applications of these approaches to China's macroeconomic data suffer from shortage of long time period quarterly GDP data. Among the limited published applications of Blanchard and Quah to Chinese data, Zhang and Wan (2005) use real industrial output as a proxy for real GDP for 1985-2000. Siklos and Zhang (2010), analyzing China's inflation fluctuation with the standard Blanchard and Quah framework and a tri-variate extension, have to limit their analysis to the short sample period of 1990-2003. The original DdPS model estimation with Chinese data use quarterly real output data that are derived from annual real GDP level by evenly allocating the annual output to the four quarters of the year.

This paper applies the above univariate and multivariate time series analyses to the estimated China's quarterly real GDP and shows that the constructed data provide a better high frequency and long period real GDP data alternative for the analyses of China's output fluctuations[12].

III. Temporal disaggregation of China's quarterly real GDP with unobserved components model

3.1 the Model

The unobserved components models are set up in terms of components that have direct interpretation of stylized features of the series. The models are capable of including trend (or long run, permanent component), cycle (short run, transitory component), seasonal components (if the data are not seasonal adjusted) and irregularities that represent the non-systematic outlier observations or measurement errors.

Following Harvey (1989), the unobserved component models for temporal disaggregation of China's real GDP can be presented in multivariate state space form as follows:

The measurement equation is:

$$y_{it}=(\tau_{it}+c_{it}+s_{it}+\gamma_{it})+\beta X_t+\varepsilon_{it} \qquad (1)$$

Or in a more general form:

$$Y_t = Z_t\alpha_t+\beta X_t+\mathrm{E}_t \qquad (1')$$

[12] To focus on the evaluation of quarterly real GDP construction, in this paper I do not include the production function approach, which may involve data problems from capital and labor statistics.

Where: y_{it}=$(y_{1t}, y_{2t,},..., y_{nt}), i = 1,2,..., n$ and $t = 1,2,..., T$ y_{1t} is the target series (y_{1t} : China's real GDP) and $y_{2t,},..., y_{nt}$ are the related series for multivariate models. Z_t is a $n \times m$ matrix, where m is the number of unobserved components, and N is the number of dependent variables in multivariate models. X_t is the matrix of assumed exogenous variables or the "related variables" which will only be present in the univariate with related series model[13]. β is the parameter vector of the explanatory variables. α_t is $m \times 1$ the state vector that contains the unobserved components that may include trend τ_t , cycle c_t , seasonality s_t, and irregularity γ_t. E_t is an $n \times 1$ vector of serially uncorrelated disturbances assumed with mean zero and the covariance matrix G_t, or $E(\varepsilon_t) = 0$ and $Var(\varepsilon_t) = G_t$

The transition equation is,

$$\alpha_t = T_t \alpha_{t-1} + H_t \eta_t \qquad (2)$$

Where $\alpha_t = (\tau_t\ c_t\ s_t\ \gamma_t)'$, T_t is a $m \times m$ matrix, H_t is $g \times m$ matrix ($g = m$ when all components are defined as stochastic, g will not equal to m when some components are defined as fixed or determinate). η_t is a $g \times 1$ vector of serially uncorrelated disturbances with mean zero and the covariance matrix, Q_t, or $E(\eta_t) = 0$ and $Var(\eta_t) = Q_t$

I use seasonally unadjusted data in the disaggregation models to avoid losing information from such adjustments. The seasonal components generated through the disaggregation will be compared with the seasonal factor generated from commonly used seasonal adjustment procedure in the evaluation section of the paper.

[13] I do not add explanatory variables to the unobserved components such as trend, cycles and/or seasonality. Adding explanatory variables means adding assumptions on the relationship of the related series, which will reduce the generality of the model of data construction.

The disaggregation models are specified with choices for stochastic drift and seasonality to capture the possible time variance of drift and seasonality[14].

Disturbances of components within series are assumed uncorrelated from each other in the disaggregate models following Harvey and Watson (1986), Harvey (1989) and Clark (1987).

Putting observations with different timing intervals into the state space form is the key step of using unobserved component model for temporal disaggregation. Harvey (1989, section 6.3) introduced the technique of using a cumulator variable for mixed frequency data in state space model. The cumulator variable for quarterly data is defined as following:

$y_t^c = y_t$, where $t = s(\tau - 1) + 1, \tau = 1,...(n/s), s = 4$

$$y_{t+1}^c = y_t + y_{t+1}$$

$$y_{t+2}^c = y_t + y_{t+2} + y_{t+3}$$

$$y_{t+3}^c = y_t + y_{t+1} + y_{t+2} + y_{t+3},$$

$$y_{t+4}^c = y_{t+4}$$

$$y_{t+5}^c = y_{t+4} + y_{t+5}$$

…

Where y_t^c is the year up to date cumulated value of the quarterly level of the series, and y_t is the quarterly level of the series. For the years with only annual data available, only y_{t+3}^c , which equals the annual level of the series, is observable. For China's real GDP, the cumulator variable y_t^c is only observed once every 4 periods during 1978-1991. The series of cumulator

[14] Fixed drift and seasonality are also tried for comparison.

variable is considered as the target series (y_{1t}) in all models. The unobserved values of y_t^c are then treated as missing observations to be estimated with smoothing algorithms from the Kalman filter.

3.2 The unobserved components specification

The general UC model specification is capable of nesting the three categories of interpolation models: Univariate models without related series, univariate models with related series and multivariate unobserved components models. Different specifications of the components are tried and the constructed quarterly data are evaluated.

The unobserved trend component can be specified as:

$$\tau_t = \tau_{t-1} + \mu_t + \eta_{\pi}, \quad \eta_{\pi} \sim iid(0, Q_{\tau}) \qquad (3)$$

There are two widely applied specifications of the slope of the trend: one is based on Harvey (1985) and Watson (1986), which assumes that the trend is random walk with constant drift, i. e., $\mu_t = \mu$; the other is the Clark (1987) model, in which the trend is assumed to follow random walk with a random walk drift, i.e. $\mu_t = \mu_{t-1} + \zeta_t$. Clark's assumption of a random walk with drift is capable of accounting for possible structure breaks. To avoid losing information in the temporal disaggregation, the choice of time varying or stochastic slope (the drift of trend) following Clark model is applied in the disaggregation models with related series[15].

The estimation starts with general local linear trend (LLT) models, which do not include cyclical component. The cyclical component is then introduced into the model and assumed following 2nd order auto-regressive process or AR (2), as for most real output series in the literature (Harvey 1985, Clark 1987 and Morley et. al. 2003). Harvey (1989) and Durbin and

[15] Fixed slope of trend is also tried for comparison.

Koopman (2001) suggest trigonometric expressions for cyclical components which are not applied in this paper, because it may introduce arbitrary waves in the cyclical components.

Thus when the unobserved cyclical component is included, the transition equation for cyclical component is:

$$c_t = \varphi_1 c_{t-1} + \varphi_2 c_{t-2} + \eta_{ct}, \quad \eta_{\mathrm{ct}} \sim iid\ N(0, Q_c) \qquad (4)$$

The correlations between trend and cycle disturbance are assumed to be zero in the temporal disaggregation models following Harvey and Watson (1986) and Clark (1987). Since I will only take the Kalman smoothing estimation results of the missing observations and not investigate the trend cycle decomposition from the temporal disaggregation, the assumption of zero cross correlations will not affect the final result of the data construction[16].

The unobserved components models are capable of handling seasonal adjustment simultaneously with the temporal disaggregation, with the underlying assumption that the seasonality relationships of the disaggregated series are consistent or homogenous with the related series along the sample period. There are two options of seasonality formulations in the Structural Time Series Analyser, Modeller and Predictor package (STAMP 8, Koopman, et al. 2007): trigonometric stochastic seasonality (Harvey 1989, 6.2), which allows for changes of seasonality pattern along the sample time, and the fixed dummy seasonality. I chose stochastic seasonality in the models, because it can track the possibility of changing of seasonality during the time period and avoid losing information for the seasonality in the constructed data[17].

[16] Assumption on the correlation of permanent and transitory shocks is critical to the estimation of permanent and transitory compositions or the unobserved components. While the data construction only take the result of the estimation of the level of the series and not doing decomposition for the series, thus will not be affected by the assumption. The zero cross correlation assumption reduces the number of coefficients to be estimated and increases the degree of freedom, thus increases the chance of convergence especially for the multivariate models.

[17] Fixed or determinant seasonality is also tried for comparison.

Measurement errors of the data can be a big concern for China's macro-economic data. Therefore I include irregularity term in the models. However, I do not find any significant irregularities in any models.

3.3 Univariate and Multivariate models

Univariate models without related series

When $n = 1$, the model is a univariate UC model and contains the cumulated quarterly real GDP level with missing observations only. The modeling starts with a Local linear Trend (LLT) univariate model without cyclical components. For LLT model, the measurement equation is simplified as:

$$y_t = \tau_t + s_t + \gamma_t \qquad (5)$$

Univariate models with related series.

The univariate model with related series as exogenous explanatory variables without cyclical component is comparable with Chow-Lin approach and its modifications (Harvey 1986). The explanatory variables enter into the measurement equation as:

$$y_{1t} = \tau_{1t} + s_{1t} + \gamma_{1t} + \beta\, x_t \qquad (6)$$

If the components are set as deterministic and ε_t as AR (1), the model is comparable with the original CL model (Moauro and Savio 2005). When there is no cyclical component included, the univariate with related series model with random walk drift is comparable with modified CL method, also known as Fernadez (1981) model. To find the best model for temporal disaggregation of China's real GDP, I also try the models with AR (2) cyclical component.

Multivariate unobserved components models

Temporal disaggregation using multivariate unobserved components models, as reviewed in section II, uses the information from related macro-economic series and at the same time avoids liner relationship assumption on the related series or the weakly exogenous as in the Chow-Lin model and its extensions. As discussed in the literature section of this paper, the multivariate UC models may be more appropriate if the cointegrating relationship is hard to find between the available related series. The problem can be more likely for emerging countries, where high frequency macro-economic data are very limited.

Another advantage of this framework is that it allows for simultaneous disaggregation, seasonal adjustment and trend cycle decomposition. While not the focus of data construction section of this paper, the common trends, cycles and seasonality among the related series can be easily imposed and tested in the multivariate UC framework.

3.4 Logarithmic transform of the data

All series values are in natural logarithms to ensure positive estimation for real GDP in the disaggregation models. First, due to the relatively small sample, a few large seasonal troughs may cause the estimated quarterly real GDP to become negative when using levels of the series[18.] Logarithmic transformation of the data guarantees positive values of the estimated quarterly data. Secondly, as Proietti 2006 shows, since logarithmic transformation reduces the heteroscedasticity of the series and the underlying assumptions of the multivariate disaggregation models include homoscedasticity on seasonality and variances among series, it is more appropriate to use for those models.

The cumulated series of the logarithmic transformed target series can be expressed as:

[18] Estimation of the models using levels of the series does generate a few negative results at certain seasonal troughs.

$ly_t^c = \log(y_t)$, where $t = s(\tau - 1) + 1, \tau = 1, ...(n/s), s = 4$

$ly_{t+1}^c = \log(y_t + y_{t+1})$

$ly_{t+2}^c = \log(y_t + y_{t+2} + y_{t+3})$

$ly_{t+3}^c = \log(y_t + y_{t+1} + y_{t+2} + y_{t+3})$,

$ly_{t+4}^c = \log(y_{t+4})$

$ly_{t+5}^c = \log(y_{t+4} + y_{t+5})$

…

$$y_t^c = \log(\phi_t y_{t-1}^c + y_t), \phi_t = \begin{cases} 0, t = s(\tau - 1) + 1, \tau = 1, ...(n/s), s = 4 \\ 1, \quad \text{otherwise} \end{cases} \quad (7)$$

Where ly_t^c is the logged cumulated level of the real GDP, and y_t^c is the cumulated level of the real GDP.

One concern about the logarithmic transformation on China's data is the relatively high growth of the series. As Banerjee et al. (1993) discussed about logarithmic transformation of time series, changes in the logarithm approximately equal to the percentage change of original levels of the series. When the changes are relatively large, logarithmic transformation may dampen the growth patterns. However, comparing the results from disaggregation with the real official data (the overlapping period 1991q1-2008q4) does not show any significant effect on the magnitude of fluctuations.

IV. China macroeconomic data

My study aims to estimate China's quarterly real GDP data in consistency with the official quarterly published data since 1992. I focus on the real output fluctuations since 1978, when China embarked on the market-oriented and openness economic reform. The annual and quarterly data used in this paper are from the National Bureau of Statistics of China (NBS), the nation's statistical authority[19], and official monetary authority and international trade statistic agency.

4.1 The official GDP data

China's National Accounts followed the Material Product System (MPS) of the former Soviet Union from 1949 until 1985. China's GDP estimation transitioned to follow the guidance of United Nations System of National Account (SNA) in 1985 and formally completed the process in 1992. The quarterly GDP data are officially published since 1992.

Empirical studies of the Chinese economy have been plagued by the problems of availability and reliability of official Chinese macroeconomic data. Despite the data challenges, it is still worthwhile to study the features of China's economy, the world's 2nd largest economy and the most populous country.

China's official GDP have been criticized for having been overstated during 1980s and 1990s (Rawski 2001, World Bank 2005, etc), understated in the middle of 2000s (Economist May 1st 2008), and then overstated again during the most recent financial crisis. Most recently, Huang (2011) argues that the true China's GDP is likely to be much higher than reported due to the understatement of consumption estimation. As a transitional economy, China has undergone continuous changes, and has complex political, social and economic structure. Despite the efforts

[19] The official data are published as cumulated year on year growth rate at comparable price. Data from 1992-2005 are from the publication of National Bureau of Statistics of China (NBS 2008).

made by NBS to improve and explain the GDP estimates over the years, confidence in the accuracy of official data quality remains the primary problem that must be addressed for empirical research on Chinese macroeconomic issues[20].

After carefully reviewing the literature on Chinese data quality and the national statistical accounting system (Appendix 1), and comparing different data resources and data construction methods[21] , I agree with many researchers (Holz 2006, Chow 2006, Klein and Ozmucur 2003) and most international organizations (OECD, IMF[22]). Although there are weaknesses or short-comings in the statistical system that derives Chinese national accounts estimation, Chinese official macroeconomic data after 1978 do not appear to be politically manipulated or systematically biased. The official data can serve as "a reliable guide" (OECD 2006) to the level and growth pattern of GDP, even though the margins of error are "certainly larger than that of the most developed countries" (OECD 2006). Any other alternative data series constructed or corrected by researchers has not been proven to be more precise or reliable (Holz 2006). When I run the dissaggregation models in STAMP, I cannot find the existence of any significant measurement errors or irregularity. Thus "Official Chinese data should be the first port of call" (Scheibe 2003) for my study. The data resources of my study, CEIC and IFS, both use the official data from China NBS as their final data source.

[20] A partial list of the recent media news and reports on China's data problem includes (from the latest):

"Reflating the dragon, can the world's fastest-growing economy avoid a sharp downturn?" Economist Nov. 15th 2008, which claims that China's official growth fluctuations are smoothed"

"An aberrant abacus—coming to terms with China's untrustworthy economic numbers" Economist, May 1st 2008, which ranks the reliability of Chinese statistics.

[21] Besides the estimation with the data presented here, I apply the same methods to data covering shorter periods and from other informal resources (the IMF World Economic Outlook dataset and Fudan University dataset). I compare the results and check if the data from different resources and the subsample data have significant different features.

[22] The World Bank criticized the Chinese national account statistics and revised their GDP estimation for China upward for 34% from the officially reported number in 1993. In 1996, the World Bank accepted China's reformed statistic system and the official GDP number again. But the World Bank revision and method of estimation was also questioned by many researchers.

The official quarterly real GDP year-on-year growths are shown in Figure 1[23]. The year-on-year real growth rates suggest that instead of "recessions" or negative growth rates at the troughs of the cycles, China's economy experienced "slowdowns" or "growth recessions" at times but always had positive growth rates during the sample period. There are five major slowdowns in year-on-year growth rates, which happened in 1980, 1984, 1989, 1996-1998 and most recently in 2008 (Chinese Academy Of Social Science, 2008-2010, Liu 2009). The slowdowns in output growth in 1984 and 1996 were accompanied by hyperinflations. The "Tiananmen Square" political chaos in 1989 significantly halted lots of the economic activities across the country. The Asian financial crisis occurred in 1998 had an adverse effect on the economic growth. In 2008, China's economic growth dropped to 6.5% in the last quarter, adversely shocked by the global financial crisis.

4.2 Related series

The only available high frequency quarterly macro-economic data for the sample period is monetary statistics and international trade statistics. To estimate the missing quarterly real GDP data for China, I consider different combinations of monetary and trade variables as related series in the multivariate UC modeling. The monetary series, including domestic credit, international reserves, M1 and M2, are available quarterly since 1978; International trade series include total exports and imports, total trade volume, which are available quarterly since 1981. Domestic credit, international reserves, M1 and M2 are nominal outstanding balance. Each series may carry different information associated with the economic development and outputs fluctuations.

[23] The data construction of this paper is based on log level data. The discussion in this section documents the information provided by the raw official real GDP data, which are published as year on year growth rates only.

The monetary and trade data used in the temporal disaggregation of GDP are not only available quarterly for the sample period, but also of good quality. According to the Economist (2008) the quality of the related series' data is among the top two most reliable official macroeconomic data of China.

Figures 2.a and 2.b shows the log quarterly and annual real GDP and the potential related series data used in the models. All data are not seasonally adjusted. The series appear to follow similar upward trend in the long run. Figure 2.c and Figure 2.d present the year on year growth rates [24] of the available quarterly real GDP with the monetary and trade related series respectively. Table 5 documents the correlations of the year on year growth rates of real GDP and the potential related series for the whole sample, data construction sample and the fully available sample period.

The correlations of the fluctuations of real GDP with most of the potential related series appear to be high and stable except exports. The close to zero correlation of real GDP and exports during 1978-1991 shows that the openness of China economy was very limited during the period. With China's expediting integration into the global economy in later years, the correlation of economic growth with exports increased substantially. All joint tests of cointegrating relationships between combinations of related series that include exports show no evidence of cointegration (Table2).

V. Temporal disaggregation model selection and estimation results

This section presents the procedure of model selections and temporal disaggregating estimation using the unobserved components model specified in section III.

[24] The real GDP data construction of this paper is based on log level data rather than growth rates. However, the relationships of series based on properties of growth rates, although they may be different from that based on the level data, provide useful information.

5.1 Unit root and cointegration tests

The procedure starts with unit root test and cointegration test for the real GDP and related series. The tests are important in finding whether Chow-Lin related series models are valid or not. As I have discussed above, the estimation of univariate models with related series (Chow-Lin method) will only be valid if there is a linear relationship between the included related series and the target series. With nonstationary series, this assumption is only valid when there is a cointegrating relationship among the series.

The stationarity of the annual logarithms level of the real GDP and related series is tested using the Augmented Dickey-Fuller (ADF)[25] . Table 1 reports the results of the ADF tests. All series appear to have a unit root in the level and are stationary in first differences.

Thus, any temporal disaggregation methods, such as the original Chow-Lin model, that not consider the nonstationarity of the series are invalid for Chinese real GDP level disaggregation. The data must be first differenced before applying those methods. Or data other than the real GDP level but stationary, such as the real growth rates used by A&R, should be used. However, important information, especially on the level and trend, may be lost during the first difference or using growth rates data. Plus the growth rates series may have difference properties than the level data.

As I discussed in section III, the unobserved component approach is not only capable of nesting the disaggregation of stationary series, but also capable of modeling the nonstationarity with different specifications of the permanent component to capture the property of the series.

[25] Other unit root tests methods lead to the same conclusion. The results are available upon request.

I then use the Johansen cointegration test to check for a cointegrating relationship among the different combination of the annual real GDP and related series. Table 2 presents the results of the tests. The tests provide evidence in favor of cointegration among the annual real GDP, total trade, imports and monetary indicators (domestic credit, M1 and M2). There is no evidence of a cointegrating relationship when including exports in the system. Including international reserves may introduce more than one cointegrating relation among the series. The existence of a cointegrating relationship among the related series ensures that the Chow-Lin method is applicable to the disaggregation of China real GDP with selected related series. Thus the univariate with related series models should be included in the model selection of temporal disaggregation.

5.2 Temporal disaggregation model selection and results

The unobserved components models for temporal disaggregation are estimated using the STAMP8 program. The program applies the Kalman filter to obtain the components of the series and uses maximum likelihood methods to estimate the parameters. Missing quarterly data are generated with smoothing algorithm of the Kalman filter.

To select the model for disaggregation, I estimate the models with different specifications of components and different combinations of related series. All models are estimated with the full sample period from 1978q1-2009q4, but missing quarterly real GDP from 1978q1-2008q4. Official quarterly real GDP for 2009 q1-q4 are used to initiate the estimation, which is required by the STAMP program[26]. Once the estimations for 1978 q1 to 2008q4 are obtained, I calculate the root mean squared standard errors (RMSE) of the estimated data and the official published

[26] The initial value can be changed but the one year official quarterly data help in finding the convergence and reduce the length of iteration procedures.

quarterly data over overlapping period 1991q1-2008q4. The best fit model for data disaggregation is then determined by the minimum RMSE[27]. Based on the selected model, I estimated China's real GDP series over the period 1978q1-1991q4. The RMSE criterion suggests the multivariate UC model including domestic credit and total trade as related series with stochastic trend and AR (2) cyclical component (Table 3). To further check the stability of the model, I replicate the model selection procedure using subsample period from 1992-2009, when the quarterly real GDP are fully observed. MUC model with domestic credit and total trade as related series is still the best fit MUC model among all MUC combinations I have tried.

Table 6 presents the parameter coefficients and variances/correlations of components estimates of the selected MUC domestic credit and total trade model, with full sample from 1978-2009 all quarterly real GDP observations missing, subsample from 1992-2009 with all quarterly real GDP observations missing and the real temporal disaggregation model on full sample with 1978-1991 quarterly real GDP to be estimated. The estimates of slope and AR coefficients are very stable cross sample periods.

Figure 3 compares the year on year growth rate of official data, comparable Chow-Lin methods and the MUC domestic credit and total trade model.

Using the selected model the final data construction estimation includes all available official quarterly real GDP observations, leaving only 1978q1-1990q4 missing.

Figure 4 shows the year on year quarterly growth rates of the final results of disaggregated real GDP, compared with series constructed by A&R. The MUC estimates has similar but a little larger fluctuations than A&R estimation, except that the growth accelerating

[27] Other statistic criteria are also shown in the table. Since the purpose of the modeling is not finding the best explanatory of GDP, the best fit of data disaggregation, or the RMSE is used to determine the selection of disaggregation model.

started from 1981 peaked in 1984q4 in my estimation, while the A&R estimation peaked 1 year later in 1985q4. Based on the annual official real growth data and the official analysis from China NBS (Xu 2010), the MUC estimation is more reliable. Bounded by the available annual level directly in the model estimation, the MUC estimates follow the observed annual level better than A&R estimates. The multivariate structural model analysis in the next section shows that this different affects the identification of the property of shocks to China's economy during this period. Both MUC estimation and A&R estimation show a big drop in the last quarter of 1989. MUC estimate drops below zero.

VI. Univariate and multivariate time series analysis of China's real GDP fluctuations using the disaggregated quarterly data

To further evaluate the quality and information provided by the MUC temporal disaggregated China quarterly real GDP data, I apply different univariate and multivariate time series analysis techniques to the quarterly real GDP data from 1978q1-2010q4, with data from 1978q1-1991q4 disaggregated from annual data by MUC model. The univariate time series analytic methods include Linear in time functions, the Hodrick-Prescott (HP) filter, the Band-pass or BP filter proposed by Baxter-King (1999) and Christiano and Fitzgerald (2003), the unobserved components (UC) techniques. The multivariate structural time series approaches are Blanchard-Quah decomposition (Blanchard and Quah 1989) and the global vector autoregressive approach building on the work of Dees et al. (2007) (DdPS approach hereafter). The MUC temporal disaggregated quarterly data provides a better alternative of high frequency real output data that covers the whole period after China's economic reform and openness, and adds valuable information to the empirical investigation on the properties of China's output fluctuations.

6.1 Seasonal adjustment

Before conducting analysis, China's quarterly real output data are seasonally adjusted using the X-12 ARIMA method.

As discussed above, temporal disaggregation with the unobserved component approach is capable of conduct seasonal adjustment simultaneously with the temporal disaggregation. Figure 5 presents the seasonal components of the logged real GDP generated from the MUC temporal disaggregation estimation and the seasonal factor based on X-12 ARIMA method. The two seasonal series are exactly the same, except slightly different at the beginning of the sample period (5 observations). The seasonal adjustment through MUC model appears to be convenient and reliable.

The X-12 ARIMA (2, 1, 2) and Tramo/seat (Time series Regression with ARIMA noise, Missing Values and Outliers/Signal Extraction in ARIMA Time series) methods also give similar results. The finding is consistent with Blades (2007), who performed similar tests on current price quarterly GDP of China. The seasonal pattern of China's quarterly real GDP is regular and predictable.

The seasonally adjusted real GDP levels are then transformed to natural logarithms. For calculation and explanation convenience, the natured log seasonally adjusted real GDP level is annualized (multiplied by 4) and multiplied by 100.

6.2 Univariate statistical filters

Economic theories on economic fluctuations and growth, including real business cycle theory, Keynesian theory and monetarism, all suggest that economies react differently to permanent shocks with long-run effects than to transitory shocks whose effects dissipate in the short run. Permanent or trend component of the real GDP is also considered as potential output of a economy, while the transitory or cyclical component is used as measures of the output gap. Understanding the relative role of permanent versus transitory movements in the macroeconomic fluctuations of the countries is important for economists, forecasters, and policy makers.

In contrast to the "classical business cycles" first defined by the Burns and Mitchell (1946) as recurrent expansion, downturn, contraction and upturn in economic activity, the "cycles" studying here follow the definition of "growth cycle", which are "recurrent fluctuations in the series of deviations from trend" (OECD Glossary). The later definition of cycle is more appropriate for China's real GDP fluctuations because the economy experienced slowdowns in growth rates but the growth rates have always remained positive. The contractions by definition should include slowdowns using a "growth cycle" definition instead of only include absolute declines or recessions in economic activity. Morley and Piger (2009) denote a more general "transitory-deviation definition" of the business cycle, which are the short-run or transitory fluctuations in economic activity around the permanent or "trend" level. The unobserved components (UC) techniques applied in this paper fit in the "transitory-deviation" definition, while the cycles isolated from the series with a statistic filter such as Hodrick-Prescott (HP) or Band-Pass (BP) filter fit in the traditional business cycle or growth cycle definition.

Linear in time (LIT) in time

As benchmark for comparison, I begin the decompositions from the most naive linear in time and polynomial in time models. The models assume a deterministic linear (or polynomial) in time trend[28]. With the LIT estimation, I check for structural breaks by applying Quandt-

[28] The linear and polynomial in time model specification is:

Andrews unknown breakpoint test to the constant and time coefficient with trimmed 15% data and find that 1992q4 is a significant breakpoint during the sample period[29]. The breakpoint is confirmed by Chow known breakpoint test. The Chow known breakpoint test on linear in time model with official annual real GDP level confirms 1993 as a significant (at 10% significant level) breakpoint during 1978-2009. There are evidences of breakpoint around the end of 1992 in both official annual data and the MUC quarterly data. This breakpoint is mostly based on true underlying economic activity rather than the data construction procedure.

In China's economic development history, 1992q4 was the start of an era of stable and high growth following the former leader Mr. Deng Xiaoping's speech on his "Tour the South of China" in early 1992. The speech re-affirmed the national policy of market oriented economic reform and openness that was halted by the 1989 "Tiananmen" square political chaos. This breakpoint thus is considered in the other trend cycle decomposition approaches and the possible different properties of the economic fluctuations before and after 1992q4 is investigated.

Hodrick-Prescott (HP) filter

HP filter is the most widely used approach of decomposition to obtain the smoothed long term trend of China's output (or potential output) and output gaps in the literatures so far. The

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$$y_t = a + \sum_{j=1}^{n} b_j t^j + \varepsilon_t,$$

When n=1, the model is linear in time model. When n=2, it is quadratic in time model.

The models are estimated with least squares method. The trend is the predicted value of y_t and the cyclical component is the residual from the estimation. The residuals are significantly auto-correlated. Although it is well known that LIT or polynomial in time models often fail to reveal the changes in slope or intercept of the trend over time, the estimations are simple and straightforward, thus still can be used as benchmarks. Since larger power polynomial in time model fit the data no better than the linear trend model, I use LIT result for comparison with results from other methods.

[29] The test is conduct in Eviews. Same exercise using Pcgive package shows similar result, the recursive estimation breakpoint Chow test with the MUC quarterly data show evidence of breakpoint around 1992q3-1993q1.

HP trend is determined by minimizing the weighted sum of the squared cycle and changes in the growth rate of the trend[30].

Although very popular and convenient, HP filter may generate artificial cycles when applied to first-order integrated series. As shown by Cogley and Nason (1995) and Park (1996), the HP filter is convenient but subject to several limitations: HP filter implicitly assumes that the business cycle of the economy is symmetric during expansion and recession time, and the assumption of periodicity is sensitive to the end of the sample period. In addition, the HP filter may generate artificial cycles when applied to first-order integrated series. King and Rebelo (1993) pointed out the arbitrarily picked smooth parameter is based on the observations of the US business cycles and may not be the optimal choice for other economies. The HP filter also is criticized for lacking fundamental economic justification and arbitrarily picking smooth parameter[31]. The cycle components are significantly sensitive to the arbitrarily set smoothness control parameter λ. The standard choice of λ=1600, which is based on the observations of US business cycles, leaves the duration of the cycles average at 4-6 years. For China real GDP data, the average durations are above 8 years with λ=1600. I tried different values for λs (8, 40) to check the sensibility of cycles (Figure 6). The magnitudes of cycle appears much bigger with λ=1600, while similar when λ is set at 8 or 40. However smaller λs make the cycle cross more frequently from the zero line. Since the λ choices are arbitrary and there is no generally accepted

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[30] I generate HP trend and cycle in E-views, where the HP filter chooses s to minimize:

$$\sum_{t=1}^{T}(y_t - s_t)^2 + \lambda\sum_{t=2}^{T-1}((s_{t+1} - s_t) - (s_t - s_{t-1}))^2$$

λ is the smoothness control parameter that penalizes the fluctuations of trend. The HP filter get smoothed and stochastic trend with is uncorrelated with the cyclical components. For quarterly data, the standard selection is λ=1600.

[31.] See King and Rebelo(1993) for optimal conditions of HP filter.

criteria for choosing λ for China's quarterly real GDP, I use the standard λ=1600 result to compare with decompositions from other approaches.

Band-Pass (BP) Baxer-King and Christiano-Fizgerald filter

Band-Pass (BP) filter, also called frequency filter (Sims 1974), isolates the cyclical component of a time series by specifying a frequency band or a range of duration for cycles. The filter takes a two-sided weighted moving average (Baxer and King 1999) of data where cycles pass through the band that is arbitrarily selected. The BP procedure does not make deterministic or stochastic assumption about the trend. The frequency of the cycle is the only criteria used to identify trend and cycle. The selection of band is critical to the decomposition results. The typical choice for quarterly data is usually set at between 6 to 32 quarters (fixed length symmetric, Baxer and King 1999), which isolates all cycles that completed greater than 6 quarters and less than 32 quarters into the cyclical component. Christiano and Fitzgerald (2003) proposed a filter that considers the nonstationary and asymmetry of the underlying data, thus is more proper for time series that have unit roots such as China's real GDP.

Unobserved component decomposition

As discussed above, the frequency filters impose assumptions that may generate artificial cycles, thus may overstate the importance of the cyclical component. The statistical filters provide very little information on the evolution of permanent or trend of the series, which is important for a fast growing and transitional economy such as China. The fast changes of China economic structure and gradually but continuously implemented economic reforms may have impacts on the economy permanently or transitorily. To understand China's output fluctuations beyond the spurious statistical filters, I apply the structural time series modeling or unobserved components modeling to further investigate the property of permanent and transitory changes of China's output.

Recent development of univariate time series econometric approaches favors "let the data speak for itself". The Unobserved Components (UC) models that I used for the temporal disaggregation are also widely applied decomposition methods (Harvey 1985, Watson 1986 and Clark 1987). These methods explicitly account for the unit roots property of the series without imposing any prior assumptions. By assuming a stochastic trend, the method capture the property of the trend for aggregate output, which for most economies, grows or changes over time and thus is not stationary in levels.

The unobserved component (UC) model, as discussed in the temporal disaggregation part of the paper, assumes a stochastic trend and stationary cycle. Although theoretically the temporal disaggregation and trend cycle decomposition can be done simultaneously with UC models, only Kalman smoothing algorithm, which uses the information from the whole sample, can be applied with missing quarterly observation of the real GDP series. Here I use both Kalman smoothing and filtering algorithms on the full sample. The Kalman smoothing calculations of China's real GDP permanent and transitory components include information from future data. The model specification is documented in appendix 2.

Figure 7 shows that the smoothing cycle is slightly larger in amplitude than the filtering cycle. The turning points are also slightly different when using the future information other than the historical information till the estimated point. The smoothing estimates, including more information from the whole sample, usually fit the data better. The filtering estimates is still very useful in forecasting when only historical information is available.

The drift and parameters of AR terms can be estimated along with the decomposition using maximum likelihood method. The parameter estimates of the models are reported in Table 5. The estimated drift term, which can be interpreted as the average growth of the trend or permanent component of China real output, is 2.46% quarterly or about 9.8% annually. The estimated autoregressive coefficients, which represent the dynamics of the cyclical components, are summed at 0.977, which implies that the fluctuations of the transitory components are highly persistent.

Figure 8 shows the most commonly used HP and BP filtered cycles of China's real GDP with MUC and A&R disaggregated data. There are slight differences in the turning pattern and magnitudes of cycles.

6.3 Comparison of output fluctuation results from different univariate time series analytic methods.

HP and BP decompositions are similar in that both isolate low-frequency fluctuations to the trend and keep certain high frequency fluctuations in the cycle. The methods impose smoothness prior assumptions on the components and thus subject to restrictions of the condition of properly using the priors. Both methods may distort the characteristics of trend and cyclical components of integrated or I (1) series (Baxer-King BP filter). The LIT, HP, BP Baxer-King and Christiano-Fitzgerald asymmetric BP filter cycles of China's quarterly real GDP generated from E-views are shown in Figure 9. The HP and BP Baxer-King cycles appear to have similar cyclical patterns in peaks and troughs, while BP Baxer-King cycle is smoother than HP cycle. Similar results have been found for output data of other countries. (See Gerlach and Yiu 2003 for Asian economies, Park 1996 for the US). The identified turning points of Christiano-Fitzgerald cycle are different from others for sample period after 1992q3. Christiano-Fitzgerald cycles turn earlier than other cycles. Christinao-Fitzgeral filter considers the I(1) property and asymmetric length of cycles during the sample period. Based on the shaded areas, which are peaks to troughs of real growth rates, the Christiano-Fitzgerald cycle appears more reasonable. I use Christiano-Fitzgerald filter result for comparison.

Figure 10 compares the estimated permanent and transitory components from HP, BP Christiano and Fitzgerald filters and the UC model.

Different decomposition methods generate similar cyclical components before 1992 but different ones after 1992. The cycle periods appear shorter before 1992 (averaged at about 4-6 years), while longer after (about 10 years for the cycle before the most recent global financial crisis)[32]. Similar to the US economy, China experienced "moderation" in economic fluctuation during the period. Explanation of this difference would be, during the earlier period, the economy had to adapt to some fundamental economic reforms and transit from full planned economy to a market oriented economic structure, and the lack of adjustment mechanism result in stronger reactions to any shocks.

All approaches identify big transitory drops in 1982, when stimulating effects from the first round of economic reforms faded, and a less negative gap in 1987, following the first peak of inflation since the reform. The late 1989 drop was a combination of hyper-inflation and political chaos. The most recent financial crisis period is first identified as spike in the transitory components based on all methods, which shows the effects of stimulation package.

6.4 Structural multivariate analysis

[32] Note that length of HP and BP cycles may just due to the choice of smoothness parameters.

The estimated China's quarterly real GDP with selected multivariate UC model also provide a better high frequency and long period real GDP data alternative for structural multivariate analyses on China's macroeconomic fluctuations. The following excises on Blanchard-Quah approach and the global VAR method (Dees, Di Mauro, Pesaran and Smith 2007, DdPS hereafter) are two examples of the structural multivariate analyses using the estimated China's quarterly real GDP data[33].

The structural VAR approach: Blanchard-Quah decomposition

Due to the shortage of long time period quarterly GDP data, the applications of Blanchard and Quah method to Chinese quarterly data either use a very short sample period of data (Siklos and Zhang 2010) or an alternative series as proxy for real output (Zhang and Wan 2005). The MUC estimation of China's real GDP fills this gap. Using the MUC estimation of China's quarterly real GDP data and inflation rate from IMF-IFS database, I derive the demand component of China's real output fluctuations using the standard Blanchard and Quah bivariate structural VAR approach for 1986-2010[34]. Compared with the literature that uses other alternatives for aggregate output of China, the new real GDP data provides more information for China's macroeconomic fluctuation for a longer time period and better coverage of the economy.

Blanchard and Quah (1989) identify structural supply shocks and demand shocks with a structural vector autoregression method by assuming that the supply shocks, which are usually driven by changes in productivity, affect the real output permanently whereas the demand shocks only have temporary impacts on output. The original Blanchard and Quah model uses the unemployment rate as the additional macroeconomic variable. Due to the shortage of reliable

[33] Due to data limitation on quarterly capital investment and employment as I mentioned in earlier sections, production function analysis cannot be conducted for the period before 2000 without data construction on those series.

[34] The quarterly CPI data are available only since 1986.

employment data, application of the approach to China and other emerging countries often use inflation as demand side related series (Bayoumi and Eichengreen 1992, Bersch and Sinclair 2011). Following these literature, I use inflation rate as additional macroeconomic series to identify supply and demand shock.

The unit root tests result indicates that the logged seasonal adjusted real GDP and logged inflation rate are integrated of order 1. The Blanchard-Quah decomposition can be applied to the bivariate VAR of first difference of logged seasonally adjusted real GDP (Δy) and inflation rate ($\Delta\pi$). The data are presented in Figure11.a and 11.b. Appendix 3 presents the model specification. The lag length selection criteria suggest including six lags in the VAR. The structural VAR is then set by imposing the Blanchard and Quah long-run restriction, assuming the aggregate demand shocks do not have long-run effects on real output.

Figure 11 shows the impulse response functions that trace out the impact on the levels of real GDP and inflation by the identified supply and demand shocks. It shows that one unit of positive demand shock increases the output by about 0.8 percent and the effect diminishes in about 4 years. One unit of positive supply shock pushes the real output up by about 1.6 percent in the long run. A demand shock results in a sharp increase in inflation and a supply shock leads to a slight drop in inflation first and then the effect quickly reverses upward. The economy would face strong same direction price level changes from both demand and supply shocks. It will be difficult for the central bank to control the inflation solely through monetary policy which mainly affects the demand side. The impulse response function results are in agreement with the results of previous studies (Zhang and Wan 2005).

The estimated forecast error variance decomposition of real output based on the MUC data provides different information about China's real output fluctuations than the decomposition based on industrial production, an alternative proxy of real output used by Zhang and Wan (2005). Based on MUC data, the output fluctuations are largely explained by aggregate supply shock, while aggregate demand shocks are the main driver of inflation changes. The share of supply shock to the variance of forecast error on real GDP is much more stable (above 60% of the variance of output fluctuations) than the result of Zhang and Wan (2005) indicated (increasing from 55% to 92% over 2 years forecasting horizon). Use industrial production as proxy for the aggregate output can be problematic for China. The share of industrial production in China's aggregate output changes dramatically during the sample period. As discussed in the data section, share of production from service sector, once trivial during early 1980s, has greatly increased to over 40% of the total GDP in recent years. Industrial production, which does not cover the service sector, could not reflect the overall properties of the macroeconomic fluctuations.

The Blanchard-Quah output gap, defined as the accumulation of demand shocks on output, can be derived using the estimated structural demand shocks and the noncumulative impulse response function. By definition, the cyclical component of the real output should be mean zero in the long run. Thus the gap is set to be closed at the mean of the Blanchard-Quah demand components. Figure13 compares the Blanchard-Quah output with HP and Christiano Fitzgerald cycles. The differences shall reflect the fluctuations caused by supply shocks within the frequency band of the statistical filters.

Figure 14 compares the Blanchard-Quah output gaps based on MUC estimation and A&R estimation. The Blanchard-Quah output gap of A&R data appears very similar to that of MUC estimated data.

Global VAR

DdPS (2007) developed a multivariate system—a global VAR (GVAR) model—to explore the international linkages among economies in an increasingly globalized world. DdPS's GVAR model for China includes the following country-specific variables as dependent variables: real outputs, inflation, interest rates, and real exchange rates. Trade weighted output, price level, equity price, interest rates and long run interest rates of the rest of the world and the world oil price enter into the GVAR as exogenous variables. The model includes two lags for all variables. The authors assume that all variables are integrated of order one. To compare the estimation results with DdPS 2007, I replicate the model using quarterly data of same sample period from 1979q2 to 2003q4.

A problem of the original DdPS model estimation with Chinese data is that the quarterly real output data are derived from annual real GDP by evenly allocating the annual output to the four quarters of the year. This simple disaggregation smoothes the quarter by quarter changes of the series, thus loses the information on the quarterly macroeconomic dynamics. I replicate the China DdPS GVAR model with the quarterly real GDP data estimated by MUC model. The result of the replication shows that the new data provide important information to the model. Simple disaggregaion of the data distorts the results[35].

Figure 15 shows the level and the first difference of logged seasonal adjusted real GDP estimated through the MUC model and the original DdPS data of logged real GDP[36].

[35] Note that the quarterly CPI data are available only since 1986. DpDS appear to construct the quarterly inflation data based on annual inflation statistics. Same situation may exist for the interest rate data as well. In this analysis I focus on the discussion of real GDP data quality. To check the difference of the estimation based on the different real GDP data only, I keep the other series the same as the original DpDS dataset. However, there may be data construction problems to other series in DpDS estimation as well.

[36] The level differences are due to the difference of base year setting. It will not affect the result of VAR estimation, which is based on the first difference of the series.

The MUC quarterly real GDP data introduce quarterly dynamics to the GVAR system. The two real GDP series move within the boundary of the same annual real GDP movement. Thus, they provide similar information on signs of the long run relationship of the variables in the cointegrating vector. Table 8 shows the evidence of cointegration of the two series (Erisson, Herdry and Tran 1994)[37]. However, the estimated effects of domestic inflation and interest rates on real output based on the MUC data are much stronger than the original DdPS data reveals[38].

Table 9 presents the estimated cointegrating vector coefficients based on MUC temporal disaggregated quarterly real GDP data and on the original DdPS data. The estimation based on MUC data and original DdPS data both find that only domestic inflation and short term interest rate are statistically significant. The high significance of domestic inflation suggests the existence of a strong Phillips curve type relationship in China's macroeconomic fluctuations.

All foreign variables are insignificant for China's macroeconomic fluctuations in the long run based on both datasets. Although rapidly integrated into the world economy, China's economic fluctuations are still mainly driven by domestic factors rather than the foreign and global factors during the sample period[39].

Appendix 4 presents the results of short run coefficients and the graphs of impulse response functions for each domestic variable in the GVAR system. The real GDP and inflation appear to be exogenous based on the MUC data estimation. While based on the original DdPS

[37] Ericsson, Hendry and Tran (1994) theoretically explain why seasonal adjusted and non seasonal adjusted data are cointegrated. The MUC real GDP and DdPS real GDP can be considered as seasonally adjusted through different procedures, thus should be cointegrated.

[38] Table A4-1 in appendix 4 shows the result of likelihood ratio tests of equality of the coefficients estimated with MUC data with the estimated coefficient original DdPS data. MUC coefficients are larger in absolute value but not significantly different from the DdPS estimated coefficients, and vise versa, which can be explained again based on Ericsson, Hendry and Tran (1994), that the two datasets can be considered as results of different seasonal adjustments and should show similar long run property of the underlying series.

[39] This result is in agreement with the result of the other two papers I coauthored with Tara Sinclair using multivariate unobserved components model to investigate the relationship of China's real output fluctuations with the US and the developed world economies using quarterly data from 1978-2009

data, only inflation is exogenous. The plots of impulse response functions for China's real GDP based on the MUC data show that the economy recovers much quicker than the original DdPS data estimated from shocks on other domestic variables. Seasonal dynamics introduced by the MUC data may cause these difference in short run analysis (Ericsson et al. 1994)[40].

VII. Conclusion

This paper provides quarterly real GDP estimates from 1978q1-1991q4 using multivariate unobserved components models. The selected disaggregation model estimates the quarterly real GDP levels of China from annual data with Kalman smoothing technique, using information from the available quarterly domestic credit and total international trade data without prior assumption of cointegration among the series. Although the traditional Chow-Lin method of temporal disaggregation is valid for China data because of the evidence of cointegration among the related series, the MUC model is found to be more efficient.

To evaluate the MUC model estimated China's real quarterly GDP data, I apply the temporal disaggregated quarterly real GDP series, lengthen by the temporal disaggregation from 1978-2010, to different univariate and multivariate methods. The constructed quarterly data are shown to be a better alternative than other proxies and estimations. The data provide valuable information to the empirical study on China's macroeconomic fluctuations.

The multivariate unobserved component temporal disaggregation approach could be easily applied to the missing data problem of other macroeconomic indicators, and to the data of other developing and transitional economies, where lack of high frequency data has been a big obstacle of macroeconomic analysis.

[40] Ericsson, Hendy and Tran (1994) provide analysis on the possibility of the difference in short run or error correction modeling due to the difference in seasonal adjustment.

Through evaluate the MUC model estimated China's real quarterly GDP that covers the 32 years since China started the economic reform and openness, the properties of China's output fluctuations can be better understood. The results of unobserved components decomposition, Blanchard-Quah decomposition, and the GVAR model suggest that supply side shocks and domestic factors play an important role in China's real output movements. Although China's economy has been widely open to the world economy, outside shocks, which may mainly be on the demand side, may have either not been as strong as that from the domestic economic reforms and productivity changes, or have been effectively offset by China's macro-economic policies.

Where is China's economy today? Is it below or above potential output or trend? The different trend cycle decompositions give different answers to this question: HP and Blanchard-Quah decomposition find that China's aggregate output since 2010 is slightly below trend, while the Christiano Fitzgerald filter and UC model shows it still slightly above permanent level. All methods of analyses show that China's economy is now very close to the potential level. The answer to whether the growth will speed up or slow down looks ambiguous[41]. Given the importance of China in the global economy, this suggests further research on China's economy is clearly warranted.

[41] Further research is desirable to better understand the features of China's macroeconomic fluctuations. In Chapter two and three I extend the study with multivariable unobserved components model on the relationship of output fluctuations with other macro-economic series. Other possible extension includes applying the multivariate approaches with inflation (the Philips curve), monetary policy indices and/or consumption.

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Figures and Tables

Table 1: Unit root test results (Augmented Dickey-Full Test on annual data 1978-2009)

Series	test statistics [a]		Lag-length [b]	Deterministic [c]
Log GDP	3.608		2	Constant
log Export	7.391		0	none
Log Import	0.439		2	constant
Log Total trade	7.332		0	none
Log M1	4.480		1	none
Log M2	2.827		1	none
Log Domestic credit	3.489		1	none
Log international reserves	0.917		4	none
dLog GDP	-4.002	***	5	Constant
dlog Export	-3.470	**	5	constant
dLog Import	-4.918	***	1	constant
dLog Total trade	-3.502	**	0	constant
dLog M1	-5.744	***	0	Constant
dLog M2	-3.547	**	0	constant
dLog Domestic credit	-4.288	***	0	constant
dLog international reserves	-4.344	***	3	constant

Note: a. * , ** and ***denote rejection of the null hypothesis of a unit root at the10%, 5% and 1% significant levels critical values respectively; Critical values for the level series without constant are -1.954 and -2.653 for 5% and 1% significance levels respectively. Critical values with constant are -2.986 and -3.724 respectively.

b. Optimal Lag length is determined by Akaike information criterion (AIC).

c. Deterministic components in the test are determined by AIC.

Table 2. Johansen Co-integration test results of annual data

Log GDP with selected combination of related series

Selection of related series in the system	Deterministic components in the cointegrating equations [a]	Hypothesized No. of CE(s)	Eigen-value	Trace Statistic	Prob.	Max-Eigen Statistic	Prob. [c]
M1, Total trade	Constant +trend	None * [b]	0.652	54.141	0.003	31.635	0.008
		At most 1	0.463	22.506	0.124	18.634	0.064
		At most 2	0.121	3.871	0.761	3.871	0.761
M2, Total trade	Constant +trend	None *	0.730	55.839	0.002	39.254	0.001
		At most 1	0.387	16.585	0.447	14.663	0.213
		At most 2	0.062	1.922	0.973	1.922	0.973
Domestic credit, Total trade[d]	Constant +trend	None *	0.630	49.016	0.011	29.792	0.014
		At most 1	0.411	19.224	0.268	15.900	0.150
		At most 2	0.105	3.324	0.836	3.324	0.836
Domestic credit, Exports	Constant +trend	None	0.532	36.590	0.186	22.754	0.121
		At most 1	0.297	13.836	0.671	10.583	0.557
		At most 2	0.103	3.254	0.845	3.254	0.845
Domestic credit, Imports	Constant +trend	None *	0.719	56.398	0.001	38.133	0.001
		At most 1	0.408	18.265	0.326	15.708	0.158
		At most 2	0.082	2.557	0.925	2.557	0.925
Intl. Reserves, Total trade	constant +trend	None *	0.770	74.395	0.000	44.151	0.000
		At most 1 *	0.515	30.244	0.013	21.678	0.023
		At most 2	0.248	8.566	0.209	8.566	0.209

Note: a. The VAR systems all include a single lag and a linear trend (a constant and trend) on each variables, selected by the deterministic components in the cointegrating equation, chosen by Akaike Information Criteron (AIC) and Schwarz criteron (SC);

b. * denotes rejection of the null hypothesis at 5% significant level. The critical values for the 5% significant level on the Trace statistic are 42.915, 25.827 and 12.518 for the null hypothesis of no cointegrating equation, at most 1 cointegrating equation and at most 2 cointegrating equation respectively; the critical values for Maximun Eigen statistics for the 5% significant level on the Trace statistic are 25.823, 19.387 and 12.518 for the null hypothesis of no cointegrating equation, at most 1 cointegrating equation and at most 2 cointegrating equation respectively.

c. The p-values by MacKinnon-Haug-Michelis (1999) p-values;

d. The combination of related series in the selected model of quarterly real GDP data estimation with multivariate unobserved component approach.

Table 3: Disaggregation model selection

	Explanatory variable	Model specification			Model comparison criterion				
		Slope	Seasonality	Cyclical component	Log Likelihood	Akaike Information Criterion (AIC)	Bayesian Schwartz Criterion (BIC)	DW test	**RMSE [c]**
Univariate models	M1-1	Stochastic [b]	Stochastic	No cycle	107.85	-8.21	-8.08	1.950	**0.0143**
	M1-2	Stochastic	Stochastic	AR(2)	111.03	-9.54	-9.40	1.998	**0.0144**
	M1-3	fixed	fixed	AR(2)	112.09	-9.52	-9.38	1.998	**0.0144**
Univariate models with Explanatory variables [a]	M1, TR [Chow-Lin comparable]	fixed	Stochastic	AR(1)	94.95	-7.15	-7.01	1.885	**0.0721**
	M1, TR[Fernandez 1981 A&R comparable]	Stochastic	Stochastic	No cycle	99.26	-8.60	-8.43	1.422	**0.0134**
	DC, TR	Stochastic	Stochastic	AR(2)	97.56	-9.12	-8.74	1.713	**0.0139**
	M2 TR	Stochastic	Stochastic	AR(2)	98.04	-8.63	-8.46	1.687	**0.0130**
	M2 IM EX	Stochastic	Stochastic	AR(2)	96.08	-8.72	-8.52	1.623	**0.0133**
	DC IM	Stochastic	Stochastic	AR(2)	97.99	-8.85	-8.67	1.581	**0.0142**
Multivariate models [d]	M1, TR	Stochastic	Stochastic	No cycle	768.98	-8.45	-8.32	1.806	**0.0163**
	M1, TR	Stochastic	Stochastic	AR(2)	773.31	-8.44	-8.30	1.815	**0.0162**
	DC TR	**Stochastic**	**Stochastic**	**AR(2)**	**806.56**	**-9.74**	**-9.61**	**1.986**	***0.0128***
	M2 TR	Stochastic	Stochastic	no cycle	796.86	-8.40	-8.27	1.981	**0.0148**
	DC EX	Stochastic	Stochastic	AR(2)	810.41	-9.17	-9.04	1.995	**0.0147**
	DC IM	Stochastic	Stochastic	AR(2)	760.95	-9.33	-9.20	1.906	**0.0207**
	DC TR M1	Stochastic	Stochastic	AR(2)	1234.03	-8.90	-8.77	1.683	**0.0249**
	DC TR IR	Stochastic	Stochastic	no cycle	1051.56	-8.59	-8.46	1.978	**0.0168**
	DC IM EX	Stochastic	Stochastic	no cycle	1067.73	-9.06	-8.92	1.950	**0.0196**

Note: a. The sample period covers 1978q1-2009q4, with only 2009 q1-q4 quarterly data observed as initiate value;

b. Stochastic slope: the slope is specified as random walk with drift

c. RMSE: Root mean square errors of the estimated quarterly data with the published official quarterly data over period 1991-2008

d. The cyclical component choice may change to find convergence

Table 4: China quarterly real GDP data: MUC model estimation, A&R estimation and the official data (1978q1-2011q2)

Quarter	MUC estimated quarterly real GDP level (2000 as base year)	Standard Errors [a]	MUC estimated year on year real growth rates	A&R estimates year on year growth rates	Official year on year real growth rates (updated 2011 Q2) [b]	Official published cumulated year on year real growth rates (updated 2011 Q2) [c]	Official annual growth rates	Annual real GDP level(2000 as base year)
1978-1	267.4	0.03216						
1978-2	310.0	0.02482						
1978-3	317.5	0.03308						
1978-4	412.0						11.7	1306.8
1979-1	286.2	0.04353	7.0	6.4				
1979-2	332.7	0.03545	7.3	7.3				
1979-3	340.9	0.03704	7.4	7.9				
1979-4	446.3		8.3	9.1			7.6	1406.1
1980-1	306.5	0.01653	7.1	7.5				
1980-2	359.4	0.04006	8.0	8.4				
1980-3	367.5	0.05357	7.8	8.2				
1980-4	482.4		8.1	7.2			7.8	1515.8
1981-1	327.4	0.03612	6.8	4.8				
1981-2	380.1	0.04336	5.8	4.1				
1981-3	384.6	0.05673	4.7	3.9				
1981-4	502.5		4.2	4.9			5.2	1594.6
1982-1	345.6	0.03061	5.6	6.9				
1982-2	407.7	0.03837	7.3	7.8				
1982-3	422.4	0.04840	9.8	9.3				
1982-4	564.0		12.3	9.0			9.1	1739.7
1983-1	377.0	0.02947	9.1	7.8				
1983-2	449.1	0.03604	10.2	9.0				
1983-3	471.0	0.04526	11.5	12.1				
1983-4	632.2		12.1	13.7			10.9	1929.4
1984-1	421.4	0.02753	11.8	14.9				
1984-2	509.4	0.03365	13.4	14.2				
1984-3	542.8	0.04210	15.2	14.0				
1984-4	749.0		18.5	15.3			15.2	2222.6
1985-1	485.4	0.02550	15.2	16.3				
1985-2	586.4	0.03114	15.1	16.3				
1985-3	610.6	0.03886	12.5	15.8				
1985-4	840.2		12.2	16.8			13.5	2522.7
1986-1	542.9	0.02325	11.8	7.3				
1986-2	650.4	0.02841	10.9	10.6				
1986-3	663.9	0.03538	8.7	8.9				
1986-4	887.4		5.6	8.6			8.8	2744.7
1987-1	593.9	0.02077	9.4	11.0				
1987-2	717.8	0.02539	10.4	10.7				
1987-3	749.6	0.03158	12.9	11.9				
1987-4	1001.6		12.9	13.4			11.6	3063.0
1988-1	666.0	0.01794	12.1	11.4				
1988-2	812.3	0.02196	13.2	12.5				
1988-3	836.9	0.02728	11.6	11.8				
1988-4	1094.0		9.2	9.5			11.3	3409.2

Continue:

1989-1	729.6	0.01460	9.6	6.2				
1989-2	866.2	0.01790	6.6	5.4				
1989-3	862.8	0.02219	3.1	3.2				
1989-4	1090.4		-0.3	0.2			4.1	3548.9
1990-1	757.6	0.01025	3.8	2.1				
1990-2	891.0	0.01259	2.9	2.3				
1990-3	900.8	0.01553	4.4	4.4				
1990-4	1134.4		4.0	7.3			3.8	3683.8
1991-1	797.1		5.2	8.6				
1991-2	957.1		7.4	8.2				
1991-3	1017.9		13.0	9.7				
1991-4	1250.6		10.2	10.3			9.2	4022.7
1992-1	905.5				13.6	13.6		
1992-2	1082.0				13.1	13.3		
1992-3	1153.2				13.3	13.3		
1992-4	1453.2				16.2	14.2	14.2	4593.9
1993-1	1042.3				15.1	15.1		
1993-2	1239.4				14.5	14.8		
1993-3	1308.2				13.4	14.3		
1993-4	1642.6				13.3	14.0	13.9	5232.5
1994-1	1176.7				12.9	12.9		
1994-2	1387.9				12.0	12.4		
1994-3	1470.4				12.4	12.4		
1994-4	1882.9				14.6	13.1	13.1	5917.9
1995-1	1317.9				12.0	12.0		
1995-2	1528.8				10.2	11.0		
1995-3	1616.0				9.9	10.6		
1995-4	2100.2				11.5	10.9	10.9	6563.0
1996-1	1461.6				10.9	10.9		
1996-2	1678.4				9.8	10.3		
1996-3	1769.1				9.5	10.0		
1996-4	2310.3				10.0	10.0	10.0	7219.3
1997-1	1613.6				10.4	10.4		
1997-2	1846.7				10.0	10.2		
1997-3	1920.1				8.5	9.6		
1997-4	2510.4				8.7	9.3	9.3	7890.7
1998-1	1736.2				7.6	7.6		
1998-2	1973.2				6.9	7.2		
1998-3	2074.5				8.0	7.5		
1998-4	2722.4				8.4	7.8	7.8	8506.2
1999-1	1894.2				9.1	9.1		
1999-2	2123.0				7.6	8.3		
1999-3	2235.1				7.7	8.1		
1999-4	2900.3				6.5	7.6	7.6	9152.6
2000-1	2064.7				9.0	9.0		
2000-2	2310.1				8.8	8.9		
2000-3	2434.0				8.9	8.9		
2000-4	3112.7				7.3	8.4	8.4	9921.5
2001-1	2240.2				8.5	8.5		
2001-2	2489.0				7.7	8.1		
2001-3	2624.3				7.8	8.0		
2001-4	3391.5				9.0	8.3	8.3	10744.9

Continue:

2002-1	2439.6	8.9	8.9		
2002-2	2710.5	8.9	8.9		
2002-3	2880.0	9.7	9.2		
2002-4	3692.8	8.9	9.1	9.1	11722.7
2003-1	2703.1	10.8	10.8		
2003-2	2946.6	8.7	9.7		
2003-3	3191.4	10.8	10.1		
2003-4	4054.0	9.8	10.0	10.0	12895.0
2004-1	2984.2	10.4	10.4		
2004-2	3281.2	11.4	10.9		
2004-3	3504.0	9.8	10.5		
2004-4	4428.1	9.2	10.1	10.1	14197.4
2005-1	3318.4	11.2	11.2		
2005-2	3636.2	10.8	11		
2005-3	3899.2	11.3	11.1		
2005-4	4948.0	11.7	11.3	11.3	15801.7
2006-1	3729.9	12.4	12.4		
2006-2	4135.8	13.7	13.1		
2006-3	4377.4	12.3	12.8		
2006-4	5565.5	12.5	12.7	12.7	17808.5
2007-1	4252.1	14.0	14		
2007-2	4754.1	15.0	14.5		
2007-3	4999.9	14.2	14.4		
2007-4	6331.4	13.8	14.2	14.2	20337.3
2008-1	4732.5	11.3	11.3		
2008-2	5264.3	10.7	11		
2008-3	5493.8	9.9	10.6		
2008-4	6799.1	7.4	9.6	9.6	22289.7
2009-1	5040.2	6.5	6.5		
2009-2	5696.5	8.2	7.4		
2009-3	6008.8	9.4	8.1		
2009-4	7572.7	11.4	9.1	9.1	24318.1
2010-1	5639.9	11.9	11.9		
2010-2	6288.5	10.4	11.1		
2010-3	6592.1	9.7	10.6		
2010-4	8302.5	9.6	10.3	10.3	26823.0

Notes: a. The standard errors are for the estimated log cumulated year up to date levels estimated by the MUC model.

b. Calculated by the author based on the official published cumulated year on year quarterly growth rates.

c. The official year on year real growth rates from 1992-2004 are from *Historical data on china Quarterly GDP estimator 1992-2005* (National Bureau of Statistics of china, 2008). Data from 2005-2011 are from the website of the NBS (http://www.stats.gov.cn/tjsj/jidusj/). All data include official revisions up to date.

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Table 5. Correlations of year on year growth rates of quarterly real GDP and potential related series

Sample period	Domestic credit	M1	M2	Exports	Imports	Total trade
1978-2009	0.35	0.43	0.38	0.19	0.49	0.43
1978-1991*	0.43	0.42	0.32	-0.02	0.56	0.51
1992-2009	0.32	0.47	0.56	0.35	0.38	0.40

Note: * official quarterly GDP real growth rates are not available during this period. Annual growth rates are used to get the correlations.

Table 6. Temporal disaggregation parameter estimates---MUC model with domestic credit and total trade (Log real GDP equation only)

	1978q1-2009q4 (all quarterly real GDP missing)	**1992q1-2009q4 (all quarterly real GDP missing**	**1978q1-2009q4 (1978q1-1991q4 real GDP missing)**
Log likelihood	**805.566**	**479.22**	**1063.98**
coefficients			
Slope	0.024	0.020	0.025
	(0.000)	(0.000)	(0.000)
AR(1)+AR(2)	0.999	0.999	0.973
Variances of components			
Level	0.0000000	0.0000000	0.0000000
Slope	0.0000000	0.0000042	0.0000013
Seasonal	0.0000001	0.0000000	0.000003
ARs	0.0000161	0.0000053	0.0000000
Irregular	0.0000000	0.0000000	0.0000000

Note: standard errors in parentheses.

Variance /correlation of cross series components for Log GDP (final model: 1978q1-2009q4 With 1978q1-1991q4 real GDP missing)

	log GDP (var)	LDCq (correlations)	LTRq(correlations)
level	0.000000	0.022340	0.096930
Slope	0.000013	0.870300	0.998500
Seasonal	0.000003	0.426000	0.280800
AR(1)	0.000000	0.000980	0.002656
AR(2)	0.000000	0.005417	0.014180
Irregular	0.000000	0.000000	0.000000

Table 7. Unobserved component model parameter estimates (maximum likelihood)

Drift(μ)	Phi1(ϕ1)	Phi2 (ϕ2)	S.E of permanent shocks	S.E of transitory shocks	Log likelihood
2.460	1.876	-0.899	0.937	0.227	-188.684
(0.087)	(0.147)	(0.151)	(0.094)	(0.210)	

Table 8: Cointegration test of DdPS data and MUC data (1979q2-2003q4)

hypotheses	Trace test	[Prob]	Max test	[Prob]
r=0	21.4	[0.005]**	21.39	[0.002]**
r≤1	0.01	[0.921]	0.01	[0.921]

Note: The tests are Johansen trace eigenvalue test and maximul eigenvalue test. ** denote the rejection of hypotheses at 1% critical value. Rejection of r=0 is evidence in favor of the existence of at least one cointegrating vector.

Table 9. Cointegrating analysis of GVAR modeling for China with MUC data and DdPS original data (1979-2003, replicating of DdPS 2007)

	MUC data estimates				DdPS estimates			
Variables	**β**	***Standard Errors(SE)***	***Chi^2(1)***	***Prob***	**β**	**Standard Errors(SE)**	***Chi^2(1)***	***Prob***
Endogeous variables								
China GDP	1				1			
China inflation	13.267	(2.180)	18.313	[0.0000]***	6.791	(1.058)	22.720	[0.0000]***
real exchange rates	0.303	(0.229)	0.916	[0.3386]	0.083	(0.129)	0.258	[0.6118]
ST interest rate of China	-43.895	(8.714)	15.464	[0.0001]***	-23.011	(4.286)	20.406	[0.0000]***
Exogenous variables								
foreign aggregate GDP	2.887	(2.749)	0.930	[0.3350]	1.747	(1.406)	1.561	[0.2116]
foreign inflation	4.998	(8.738)	0.242	[0.6230]	1.464	(4.327)	0.091	[0.7626]
foreign real equity price	-0.114	(0.258)	0.157	[0.691]	-0.096	(0.142)	0.462	[0.4968]
foreign ST interest rates	21.501	(12.191)	1.580	[0.2088]	9.835	(5.986)	1.442	[0.2298]
foreign LT interest rates	-24.928	(23.187)	1.103	[0.3140]	-7.452	(11.557)	0.368	[0.5442]
oil price	0.211	(0.170)	1.466	[0.2260]	0.076	(0.085)	0.730	[0.3929]
TREND	-0.049	(0.024)	2.647	[0.1037]	-0.038	(0.012)	5.849	[0.0156]**

Note: Note: *. **,*** indicate the rejection (at the 10%, 5% and 1% critical values) of the null hypothesis that a particular coefficient is zero. The tests are based on the likelihood ratio statistic that are asymptotically distributed as Chi^2 (1).

Figure 1. China's most recent revised official annual and quarterly real GDP year on year growth rates (the shaded areas are "slowdown eras")

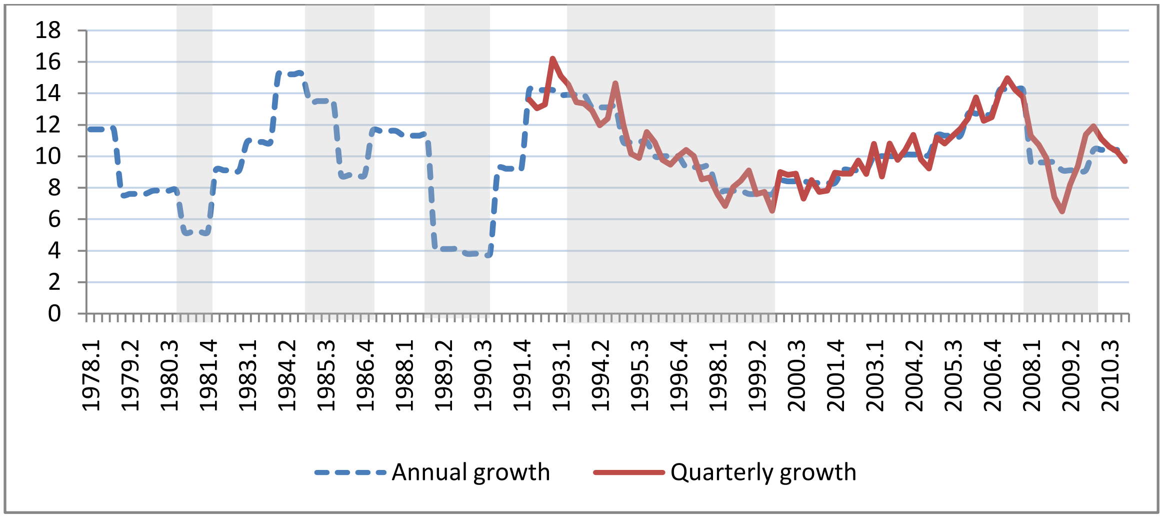


Figure 2a. The log quarterly real GDP (2000 as base year) and the potential related series.

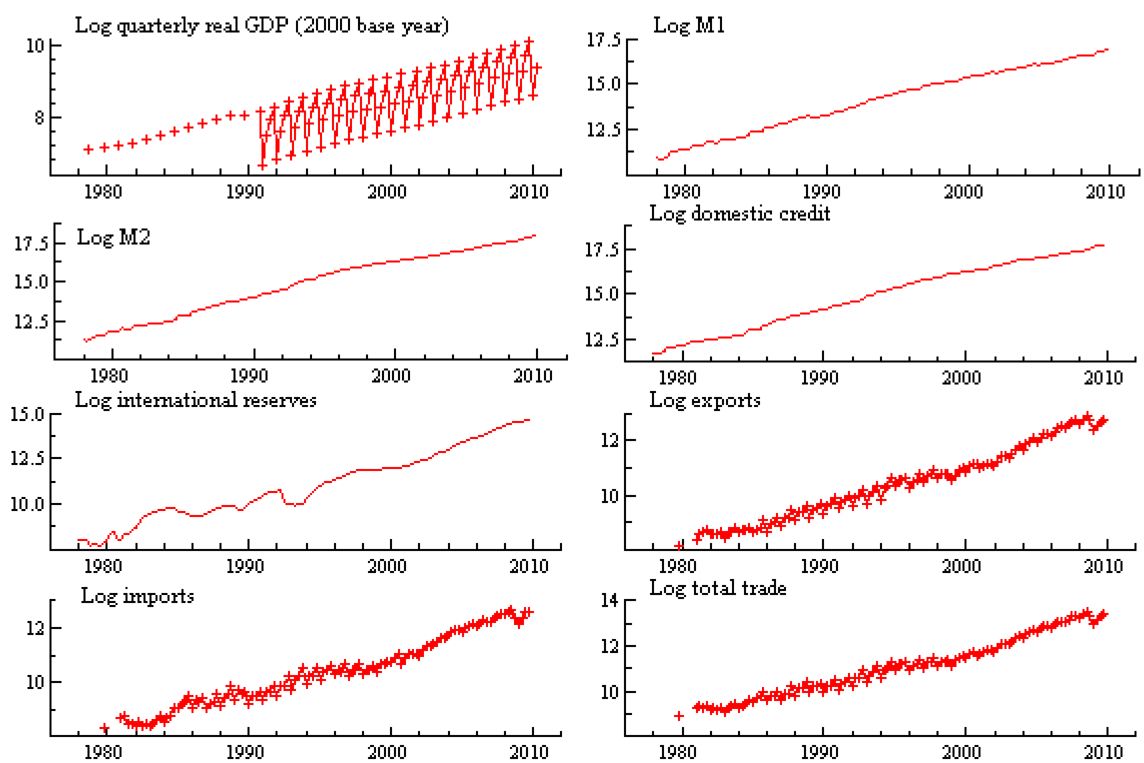


Figure 2b. Log annual data

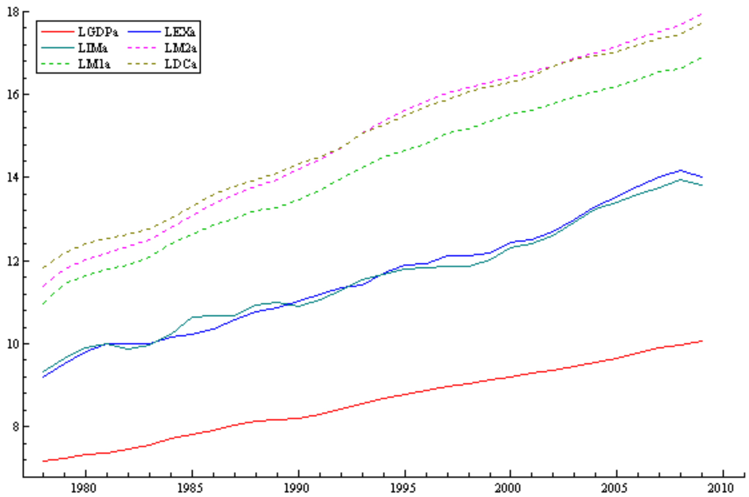


Figure 2c: quarterly year on year growth rates of real GDP with monetary related series (the shaded areas are "slowdown eras")

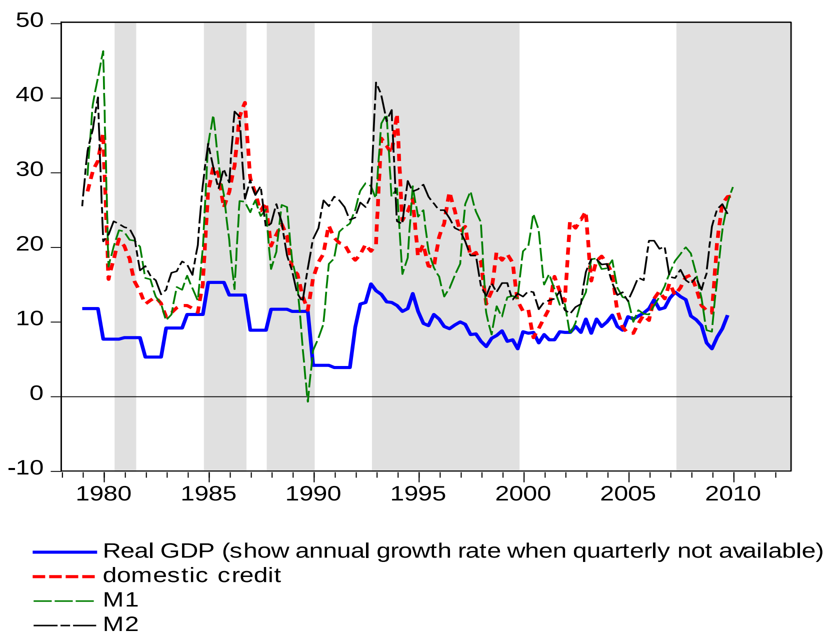


Figure 2d: quarterly year on year growth rates of real GDP with international trade related series (the shaded areas are "slowdown eras")

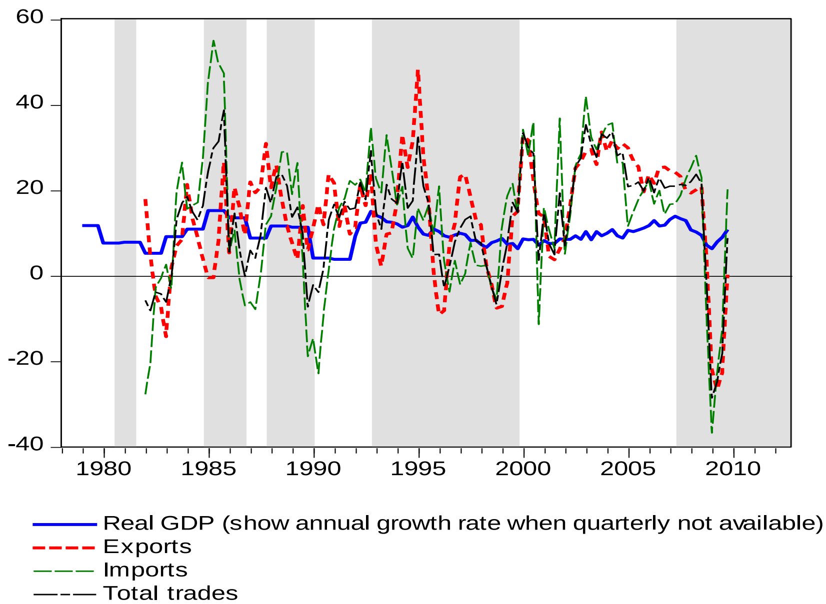
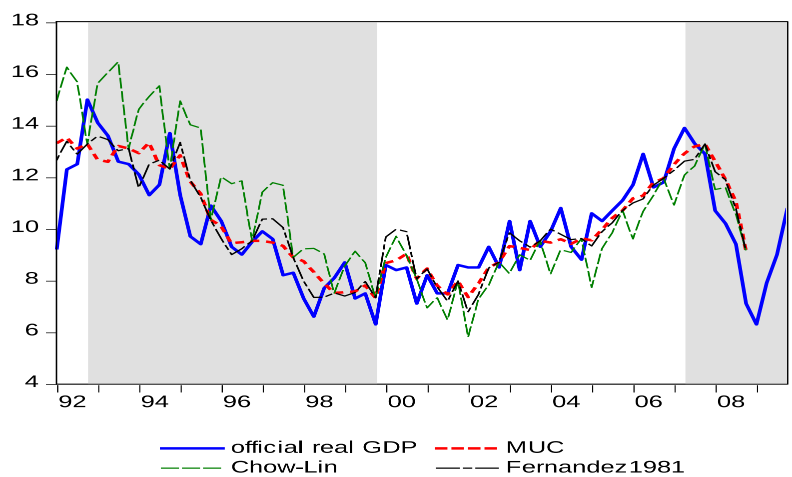


Figure 3. Disaggregation model selection: Year on year quarterly growth rates (%) 1992-2008



Note: Year on Year quarterly growth rates are calculated as $g=\log(Y_t)-\mathrm{Log}(Y_{t-4})$

Figure 4. Year on Year quarterly growth rate (comparing with A&R from 1979-1991)

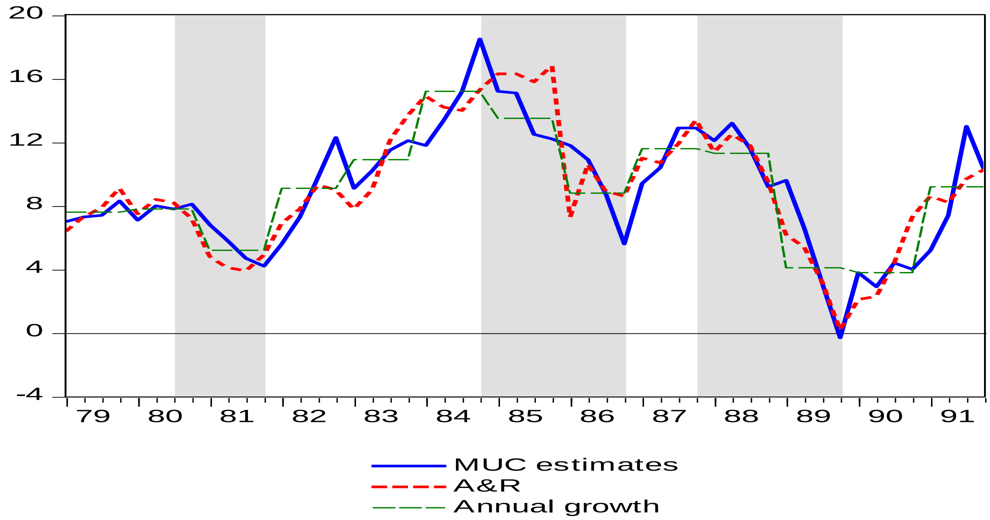


Figure 5 Seasonal factors or China's quarterly real GDP MUC temporal disaggregation model and X12 seasonal adjustment method

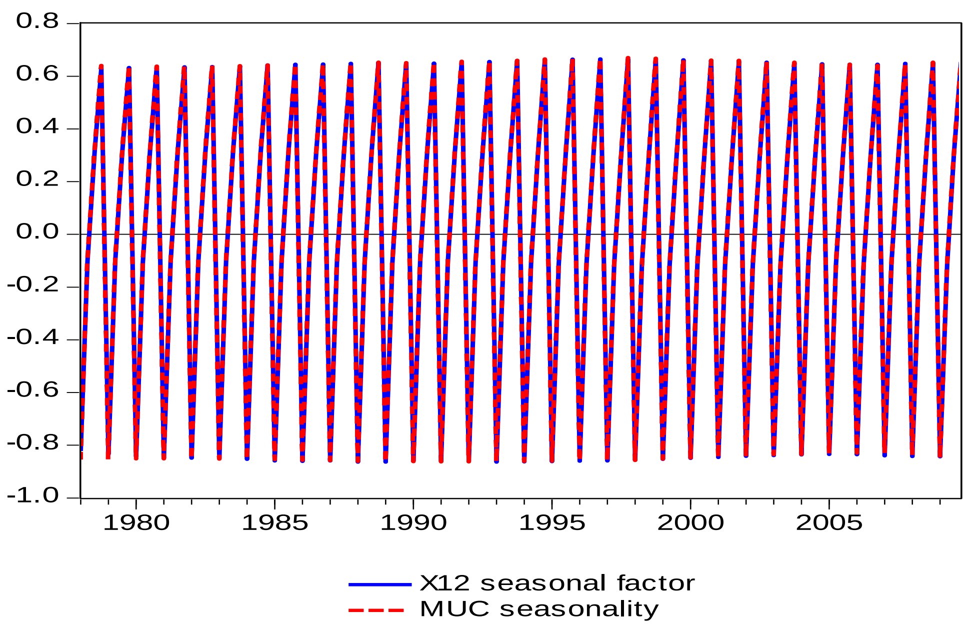


Figure 6. HP cycles with different value of λ

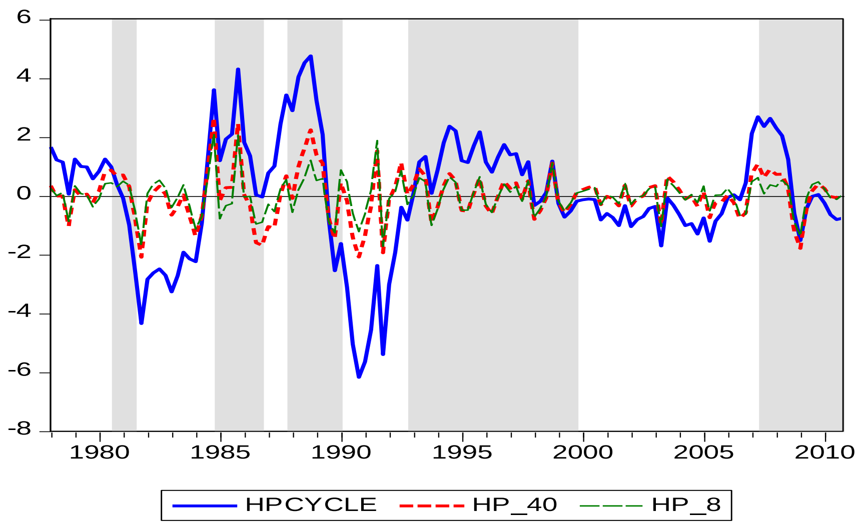


Figure 7. Unobserved components decomposition: filtering and smoothing

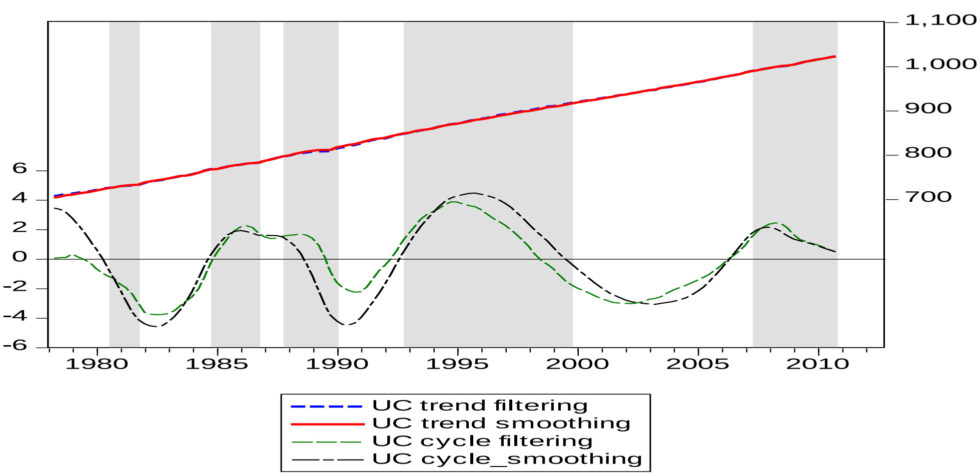


Figure 8. HP and Christiano-Fitzgerald cycles of MUC temporal disaggregation and A&R estimation of China's quarterly GDP 1978-1992

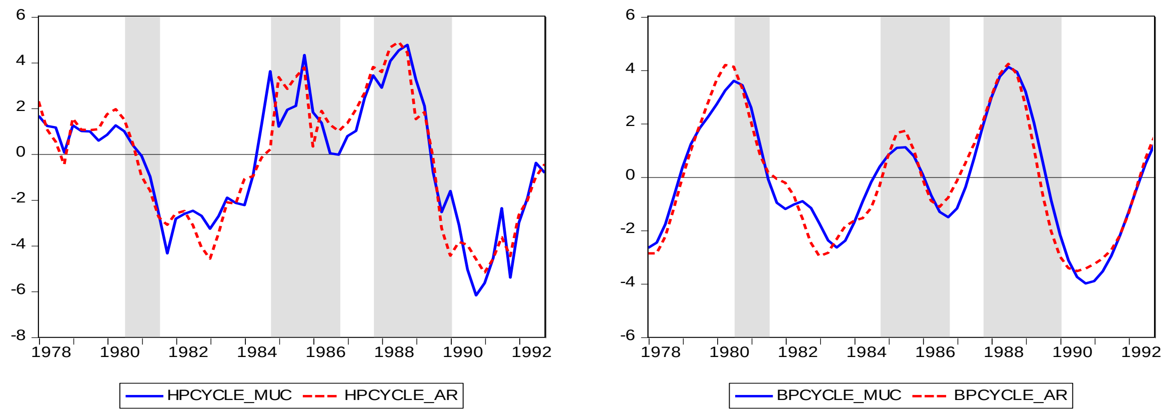


Figure 9. Linear in time residual, HP and BP cycles

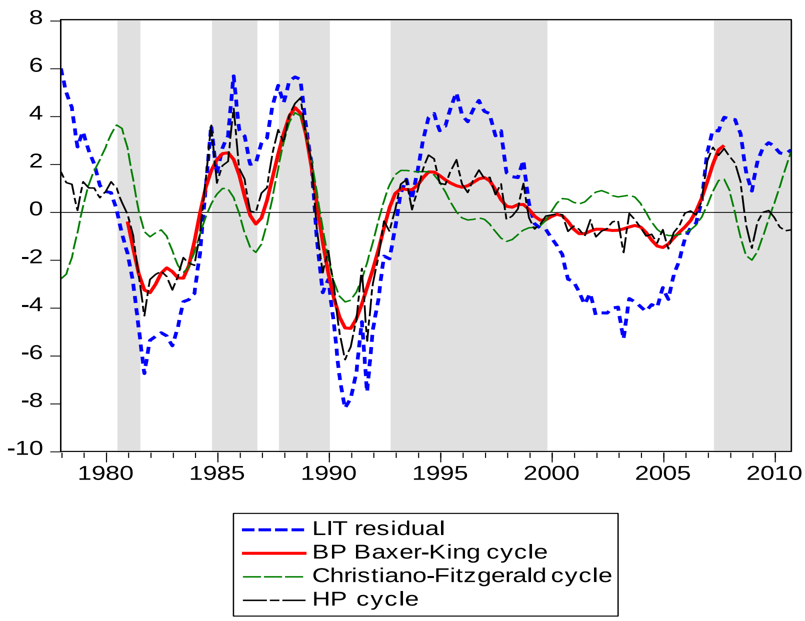


Figure 10. HP, Christiano-Fitzgeral and UC cycles

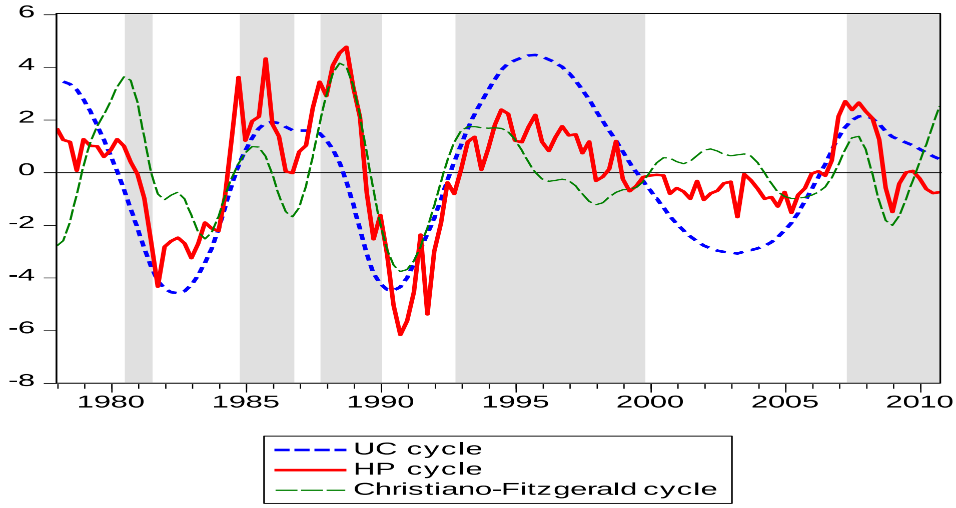
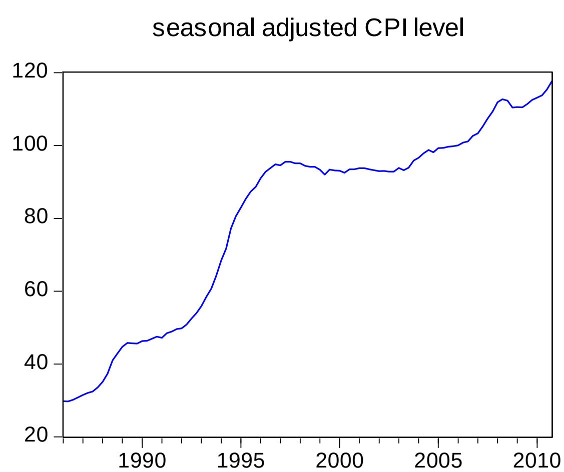
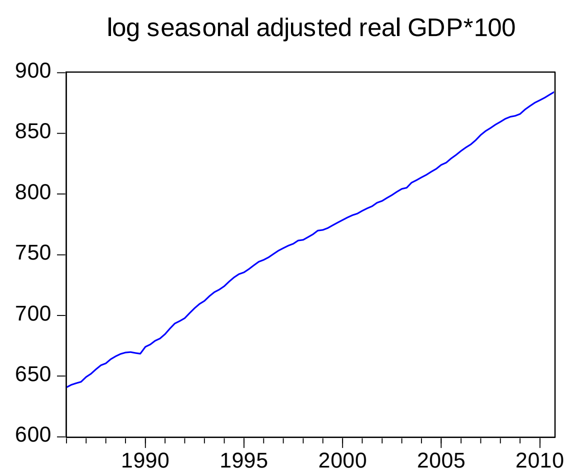


Figure 11 a. Seasonal adjusted inflation (CPI) and real GDP level 1986-2010





11. b. First difference of log seasonal adjusted inflation and real GDP 1986-2010

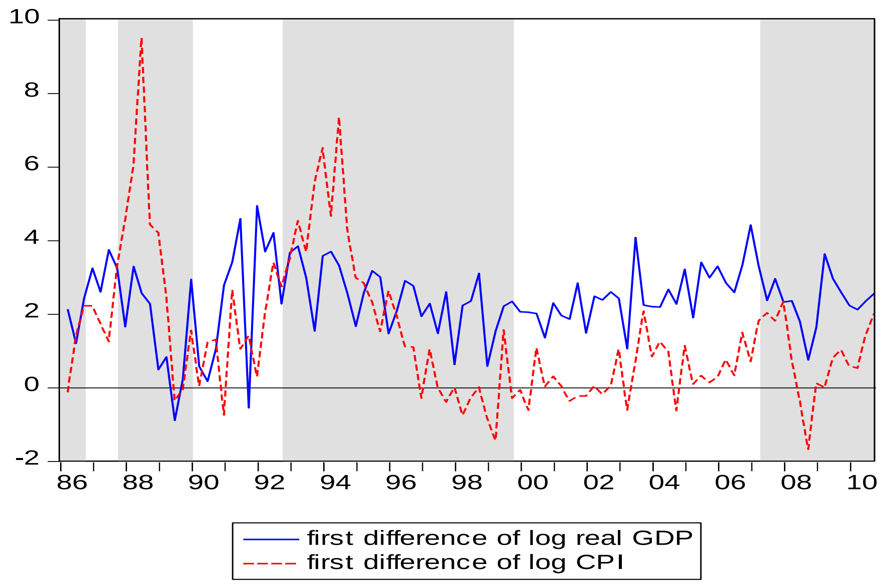


Figure12 Impulse responds functions on real output and inflation

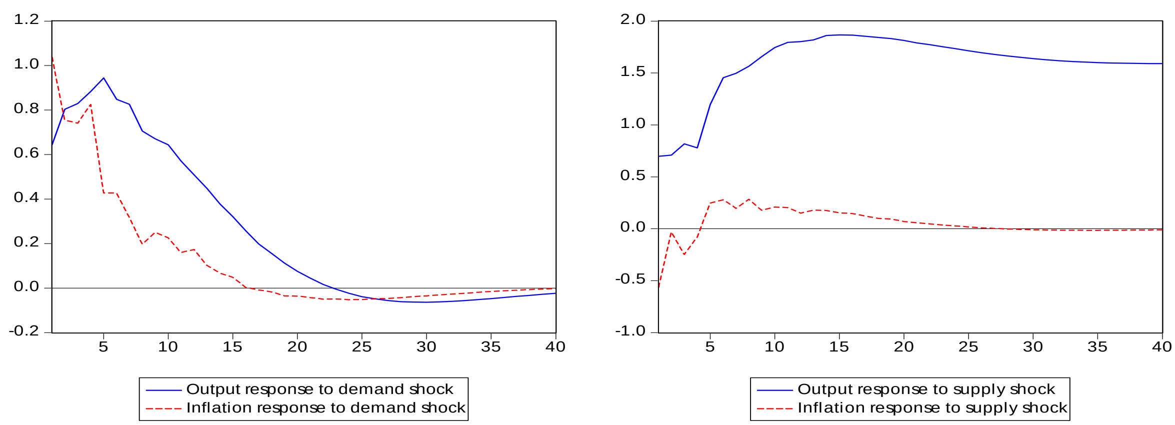


Figure13. Blanchard-Quah output gap with HP and Christiano-Fitzgerald cycles

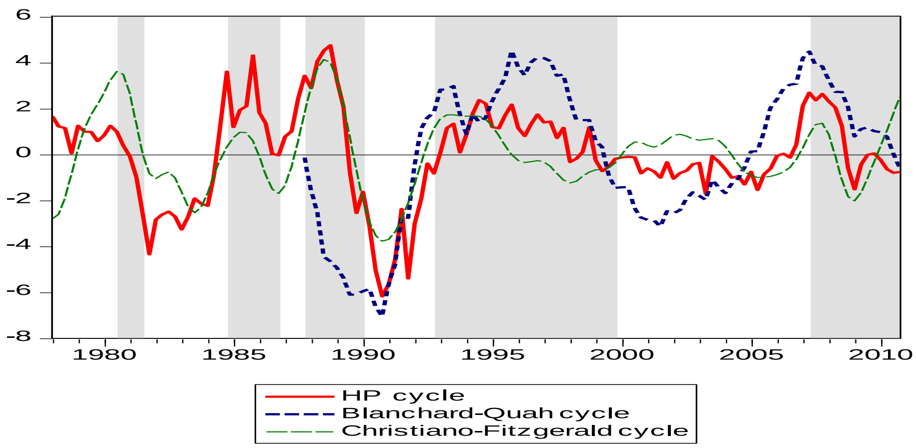


Figure 14 Blanchard and Quah cycles based on MUC data and A&R data

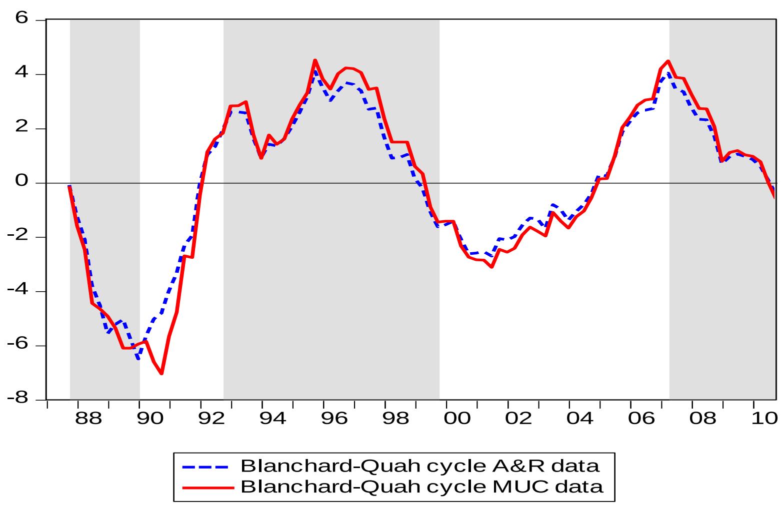
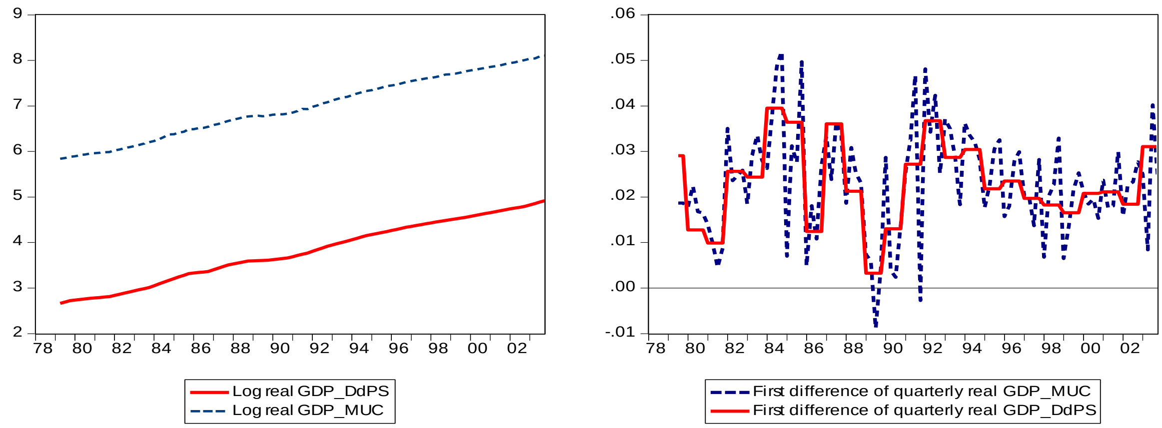


Figure 15. The DdPS quarterly real GDP data and the MUC estimated quarterly real GDP data



Note: The difference of levels is due to the difference of the base year setting of the two datasets. It will not affect the VAR analysis, which uses first difference of the series.

Appendix 1-1: Literature review on studies of China's macro data quality

The quality of Chinese data did not draw much attention from researchers outside China until the late 1990s, when China kept growing at exceptionally rapid rates of growth, averaging over 8% annually. In the early 2000s, heated discussions [42]on the quality of Chinese macro data generated a large number of publications on this issue.

The criticisms[43] of China's official data are based on evidence from alternative GDP calculations (Maddison 1998, Wu 2000, Young 2003,), and comparison with energy and transportation consumption data (Rawski 2001). One source of falsifications in the data is from the local level. For example, local government officials have incentives to report inflated numbers to meet the targets of five year plans. In the media, people are also concerned about the quick publication of GDP data, usually only two weeks after the end of reporting periods. The release of the preliminary national account data for such a big economy is considered remarkable (Economist 2008)[44.]

Studies by Rawski (2001) and Maddison (1998) are two of the most influential publications. Rawski has followed the Chinese data issue since 1976 (Rawski 1976) and is one of the most cited authors on Chinese economic data problems. Rawski (2001) challenges the official statistics by checking the quantitative consistency over output, energy use, employment and price index. Rawski and Xiao (2001) and Wang and Meng (2001) point out the possible falsifications at the local level[45]. Holz (2004) and Keidel (2001) question the official GDP

[42] Example of the discussion is the collection of papers on Chinese economic statistics in China Economic Review 12(2001), reviewed and summarized by Rawski and Xiao (2001)

[43] See Holz (2006) for a detailed survey of recent literature.

[44] The most recent official announcement on the timing of revisions of the quarterly data has become more cautious and leaves more time for the first and final revisions of the number.

[45] The possibility of a number emanating from the central government mentioned by media reports (Economist 2008) is considered low in the academic literature. The Chinese commentaries from central government has explicitly recognized local

estimation from the components, especially the household consumption data of the expenditure accounting approach. Maddison (1998) offers an alternative real GDP for China from 1952 to 1995, through checking the real growth rates sector by sector. Maddison gets a 2.5% lower average annual real GDP growth rate than the official growth rate for years 1978-1995. Maddison's estimates are used in the Penn World Tables (PWT) Version 6 which was used widely by researchers on cross-country studies. The major differences of Maddison's sector growth rates and the official ones are in "other services" and industry. Maddison uses employment, which has been criticized by Holz (2004) as invalid, as an alternative indicator for output growth. Holz argues that the assumption of zero labor productivity growth in Maddison's estimation is not valid.

Although the Chinese statistical authorities explain most of the questions as lack of understanding of China's transitional statistical system and nature of the transitional economy, they do acknowledge several problems with its GDP statistics (Xu 2002 and Xu 2004). These include lack of tracking and accurate measurements on housing services, fiscal subsidies and non marketable welfare services provided within economic entities, weakness in rural small enterprises statistics and livestock products, as well as the possible falsification at the local level. For example services that used to be provided within state-owned enterprises or commodities highly subsidized (such as housing and food) during the late 1970s and early 1980s are now mostly evaluated at market values. This can cause measurement inconsistency problems for the GDP data (Xu 2002).

The criticism and discussions urged the Chinese statistical authorities to launch a comprehensive economic census in 2004, after about 10 years since the 1995 tertiary sector

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statistics problems (Rawski and Xiao 2001). The NBS has stopped using local data to generate national economic growth data from 1998. (Xu, 1999) census. The results of the census led to later revisions in the data, sources and methods. Contrary to most of the studies stating the official growth rates are overstated, the official real growth rate estimation of year 1995-2004 were revised significantly upward in 2006. This was based on the information collected from 2004 economic census. The census results indicate that untracked economic activity, mainly in the services sector, is growing fast and accounts for a larger share than previously estimated of the economic activity.

Xu (2009), an NBS official, acknowledges several problems still exist in the service sector, price indices, quarterly GDP estimation and regional GDP estimation. In his other publication, Xu (2008) lists the current differences between China's GDP measurements and the 1993 UNSNA standards. The above problems are considered common in developing and transitional economies and should not imply that the errors of China's GDP estimation are larger than other developing economies.

Although the media still frequently questions Chinese official data, many researchers in the academic studies in recent years find that Chinese GDP data problems are not unique to China and there is no robust evidence for concluding there is systematic data manipulation or data falsification (Holz 2005 and 2006, Chow 2006). The most recent evidence on the reliability of Chinese data is from Curtis and Mark (2010), who find that China's economic fluctuations have not deviated much from the standard business cycle models using official aggregate and provincial level data, which means the data are not inconsistent with economic theory.

With the establishment of a more scientific statistical system including regular surveys and better financial statement reports for enterprises, the quality of Chinese macro statistics continue to improve. Manipulating statistics to meet political objectives, the most common concern, is more difficult at least at the national level. Xu Gao from the World Bank in the official blog [46]provides evidence of the consistency of data from different government institutes in recent years. After working with China's national account statisticians for about two decades, OECD (2006) was convinced that although there are weaknesses in the system, data manipulation does not happen at national level.

One of the big concerns for China's GDP growth is why the Chinese economy grows mostly near the government target? One specific feature of Chinese economy should be noted: although pursuing market-oriented reforms for more than 30 years, the level of government control of the economy is still relatively high. The political system and the government institutional structure also largely ensure that government investment and expenses, economic activities of state owned or controlled enterprises follow the goal of economic growth set by the government. The close to the target economic growth can be result of these government influenced economic activities.

Caution about the data

Although I agree that the official data are the best available and not systematically biased, Cautions must be taken when using the official output data based on the following considerations, in addition to the problems acknowledged by the authorities mentioned above:

First, China's statistical system and national account data compilation system are still in a transition from a pure reporting system for a centrally planned economy to a system that follows international standards[47]. Transition and reforms in the economy and the statistical system may

[46] http://blogs.worldbank.org/eastasiapacific/are-chinese-statistics-manipulated

[47] For detailed prescription and comments on the transformation of institutional organizations and data completion methods in China, see Holz (2006). See Xu 2002 and Xu 2004 for the NBS explanation about data compilation methodology and officially recognized problems. The system for the planned economy was Soviet Material Product System and the standard China's statistics following now is Standard National Accounts (SNA)

result in problems of consistency and comparability of data overtime. Note that the issue has been partly mitigated by more frequent survey and economic census.

Second, the service sector was very limited in breadth and depth before 1978, whereas it accounts for more than 40% of total output in 2010. This problem of accurate service sector data sources is highly focused in the national economic surveys. Still, there are a lot of weaknesses and emerging problems in this sector. For example informal economic activities may still cause more potential data problems for this sector.

Third, for real GDP data, the reporting system for state owned sectors still has MPS features and relies largely on enterprise reporting. For example, output in constant prices is reported by many enterprises at equal rates of nominal and real change over years due to the difficulty of calculation with correct deflators [48] (Woo 1998, Xu 2004). Although modern statistical methods such as regular surveys are being established, inconsistency in valuation of real output may still exist.

Fourth, although there is no evidence of systematic manipulation of national level data, the political events and the communist party administrations may cause some irregularities in the data. It is always necessary to check irregularities of the data in the model. Significant irregularities in the real GDP series have not been found in the temporal disaggregation models, partially due to the stochastic specifications of the components of the models, and also might due to the "Gradualism" of China's economic transition.

[48] Bosworth and Collins (2007) test this reporting problem by using alternative price index constructed by Young (2003) and find the problem may affect only on secondary (industry) sector.

Appendix1-2. the unobserved components decomposion model

As discussed in the data disaggregation part, the measurement equation of the UC models is:

$$y_t = \tau_t + c_t$$

Where τ_t is the unobserved trend component and c_t is the unobserved cycle component.

The data disaggregation estimation shows that the variation of drift term is insignificant and close to zero, thus here I follow Harvey (1989) and Watson (1986) and assume a constant drift term for the trend, the model's transition equations are specified as[49]:

$$\tau_t = \tau_{t-1} + \mu + \eta_t$$

$$c_t = \varphi_1 c_{t-1} + \varphi_2 c_{t-2} + \eta_{ct}, \quad \eta_{ct} \sim iid\ N(0, Q_c)$$

For both models, $\eta_t \sim \text{iid N}(0, \sigma_\eta^2)$; and $\varepsilon_t \sim \text{iid N}(0, \sigma_\varepsilon^2)$;

The correlations between trend and cycle residuals, interpreted as shocks or innovations to trend and cycle respectively, are assumed as zero[50].

[49] While the Clark (1987) model specification is:

$$\tau_t = \tau_{t-1} + \mu_{t-1} + \eta_t \text{ and } \mu_t = \mu_{t-1} + \upsilon_t$$

$$c_t = \emptyset_1 c_{t-1} + \emptyset_2 c_{t-2} + \eta_{ct}, \ \eta_{ct} \sim \text{iid N}(0, Q_{\eta\tau})$$

i.e. the drift of the trend is a random walk.

[50] Morley et al. 2003 introduce correlation between permanent and transitory shocks in to the model, which is an important release on the restrictions of the model. In the authors' papers on the relationship of China's economic fluctuations with the US and the aggregate output of developed countries (coauthored with Tara Sinclair), external series, such as the US real output, developed countries real output, oil price and global volume of trade, are added in a bivariate UC model with correlated cross components shocks to help the identification of the correlation of the permanent and transitory shocks for China's real output. In this paper, to evaluate the contribution of MUC temporal disaggregated data I focus on apply the MUC data to the most commonly used univariate analytic method and compare the results of MUC data with the literature.

Appendix1-3. Standard bivariate Blanchard-Quah model and decomposition

First, an unrestricted VAR model is formed as:

$$Y_t = \phi_0 + \sum_{i=1}^{p} \phi_i Y_{t-i} + e_t , \quad E e_t e_t^{'} = V$$

$$Y_t = \begin{pmatrix} \Delta y_t \\ \Delta \pi_t \end{pmatrix}, \quad e_t = \begin{pmatrix} e_{yt} \\ e_{\pi t} \end{pmatrix}$$

Where Δy_t is the first difference of log seasonal adjusted real GDP and $\Delta \pi_t$ is the first difference of the log inflation rate.

The parameters Π, residuals e_t and the variance-covariance matrix V can be obtained by the OLS estimation of the unrestricted VAR. The structural VAR then can be set up as:

$$A e_t = B u_t$$

$$B = \begin{bmatrix} B_{11} & B_{12} \\ B_{21} & B_{22} \end{bmatrix}, \quad u_t = \begin{pmatrix} u^s \\ u^d \end{pmatrix},$$

Where u^s and u^d are the assumed orthogonal or uncorrelated shocks, in this exercise the supply shocks and demand shocks (they also can be monetary shocks or external shocks, based on the endogenous variables in the VAR). Thus, $E u_t u_t^{'} = I$ and $BB' = V$. The variances of the demand and supply shocks are normalized to one.

To recover the two different shocks, we need to indentify B. There are four unknowns in B, While only three restrictions (by assuming the structural shocks are uncorrelated and the normalization of the variances). Blanchard and Quah (1989) proposed the identification method on long -run impact of the orthonormal shocks to help identify B. The accumulated long-run response C to the structural innovations takes the form:

$C = \hat{\Pi}_{\infty} A^{-1} B$, where $\hat{\Pi}_{\infty}$ is the estimated accumulated responses to the reduced form shock e_t.

Imposing a restriction of $C_{12} = 0$ can be explained as the long-run response of the jth variable to the ith shock is zero[51].

The growth in the output gap is given by:

$$\Delta y_t^{gap} = \sum_{i=1}^{\infty} B_{12} u^d$$

In the exercise, I sum over only 40 periods responds (responds over 40 periods are near zero, thus extending the sum periods won't make significant difference to the result). To obtain the levels of output gap, the Δy_t^{gap},are summed up to t and the zero line is closed at the mean of the Δy_t^{gap} [52].

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[51] Note if using Eviews to estimate the SVAR, A is set to be identity matrix.

[52] In the literature, the decomposition is called "historical decomposition"

Appendix1-4: More results from the GVAR model estimation with MUC and DdPS data.

MUC data estimation results in much stronger effects from all variables than the original DdPS data, however tests of equality of cointegrating coefficients (Table A4-1) shows that there are no discrepancies in the direction and significance of the effect.

Table A4-2 presents the short run or error correction model coefficient estimations for the four endogenous variables in DdPS model for China, based on the two datasets. Estimations of coefficients of the real GDP based on MUC data are very different from that based on the DdPS data. The estimated coefficients for equations of other variables do not change substantially. Real GDP appears to be exogenous based on the MUC data estimation.

Impulse response functions on China's real GDP (the first column of Figure 4A-1) also shows difference of the response of China's real output to shocks from other variables based on the two datasets. Not only the economy recovers much quicker, but the direction of the response to shocks from short term interest rates is different[53].

[53] Further investigation on the data of China's inflation and interest rates should be done before making any conclusion on the economic meaning.

Table 4A-1. Likelihood ration tests on the equality of cointegrating coefficients estimated by GVAR modeling for China with MUC data and DdPS original data

Hypothesis	MUC coefficients= DdPS estimated coefficients		DdPS coefficients= MUC estimated coefficients	
Variables	***Chi^2(1)***	***Prob***	***Chi^2(1)***	***Prob***
Endogeous variables				
China GDP				
China inflation	0.538	[0.4633]	0.582	[0.4454]
real exchange rates	0.916	[0.3386]	0.760	[0.3833]
ST interest rate of China	0.583	[0.4453]	0.625	[0.4293]
Exogenous variables				
foreign aggregate GDP	2.078	[0.7795]	0.209	[0.6475]
foreign inflation	0.115	[0.7340]	0.329	[0.5662]
foreign real equity price	0.003	[0.9538]	0.014	[0.9074]
foreign ST interest rates	0.519	[0.4715]	0.871	[0.3506]
foreign LT interest rates	0.363	[0.5470]	0.586	[0.4440]
oil price	0.534	[0.4649]	0.796	[0.3724]
TREND	0.087	[0.769]	0.238	[0.6258]

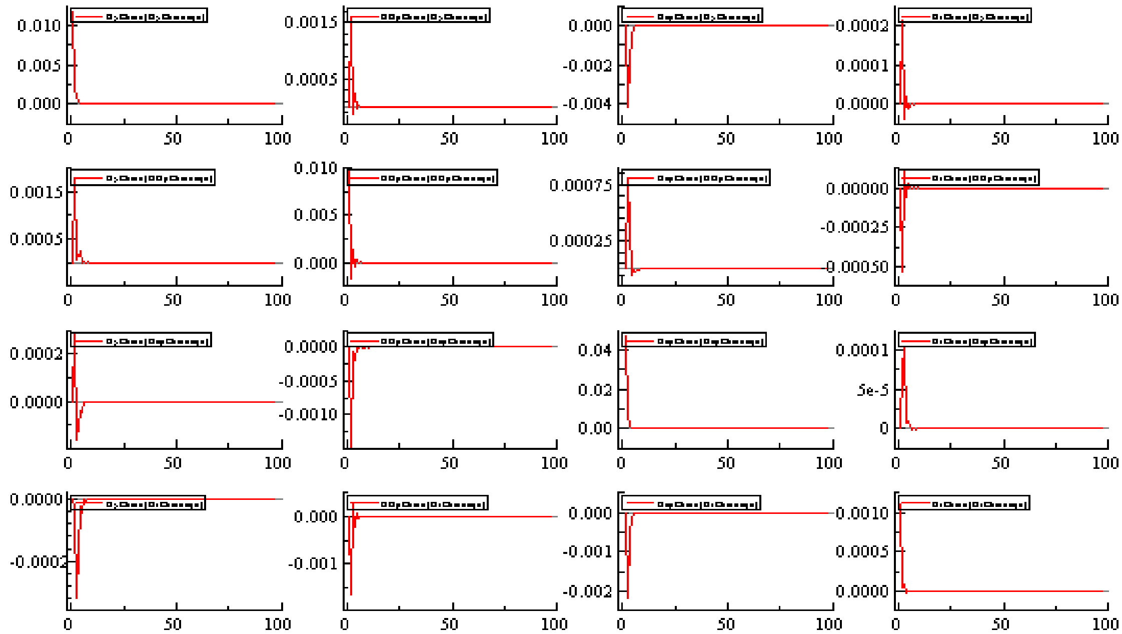
Table 4A-2: Short run error correction equation coefficients of GVAR estimated based on MUC data and DdPS data

	MUC data estimates				DdPS data estimates			
Short run equation for:	**China Real GDP**							
	Coefficient	**Std.Error**	**t-value**	**t-prob**	**Coefficient**	**Std.Error**	**t-value**	**t-prob**
China real GDP t-1	0.209	0.113	1.850	0.067	0.815	0.064	12.800	0.000
China inflation t-1	0.182	0.150	1.210	0.229	0.152	0.068	2.230	0.029
real exchange rates t-1	0.006	0.026	0.232	0.817	-0.007	0.012	-0.618	0.538
China ST interest rate t-1	-0.025	0.978	-0.025	0.980	0.682	0.449	1.520	0.133
foreign aggregate GDP	0.078	0.281	0.279	0.781	-0.095	0.130	-0.729	0.468
foreign inflation	0.204	0.346	0.588	0.558	-0.074	0.159	-0.465	0.643
foreign real equity price	-0.010	0.021	-0.475	0.636	0.004	0.010	0.456	0.650
foreign ST interest rates	-0.093	0.660	-0.142	0.888	-0.157	0.294	-0.533	0.595
foreign LT interest rates	-0.581	1.517	-0.383	0.702	-0.181	0.698	-0.260	0.796
World oil price	0.001	0.010	0.108	0.914	0.007	0.005	1.440	0.153
ECM term t-1	-0.020	0.014	-1.470	0.145	-0.020	0.006	-3.100	0.003
constant	0.208	0.130	1.610	0.111	0.190	0.060	3.180	0.002
Short run equation for:	**China inflation**							
China real GDP t-1	0.136	0.094	1.460	0.149	0.258	0.113	2.280	0.025
China inflation t-1	-0.177	0.125	-1.420	0.160	-0.162	0.121	-1.330	0.186
real exchange rates t-1	-0.031	0.022	-1.430	0.156	-0.032	0.022	-1.500	0.136
China ST interest rate t-1	-1.484	0.813	-1.830	0.071	-1.456	0.799	-1.820	0.072
foreign aggregate GDP	0.274	0.233	1.180	0.243	0.216	0.232	0.933	0.353
foreign inflation	0.634	0.288	2.200	0.030	0.606	0.283	2.140	0.035
foreign real equity price	-0.016	0.018	-0.910	0.366	-0.017	0.017	-0.973	0.334
foreign ST interest rates	-0.677	0.548	-1.230	0.221	-0.803	0.523	-1.540	0.128
foreign LT interest rates	1.574	1.261	1.250	0.215	1.711	1.240	1.380	0.171
World oil price	-0.017	0.008	-2.080	0.041	-0.016	0.008	-1.950	0.054
ECM term t-1	-0.004	0.011	-0.350	0.728	-0.006	0.011	-0.530	0.597
constant	0.033	0.108	0.302	0.763	0.049	0.106	0.462	0.645
Short run equation for:	**China real exchange rate**							
China real GDP t-1	-0.352	0.456	-0.772	0.442	-0.248	0.562	-0.441	0.660
China inflation t-1	0.083	0.608	0.136	0.892	0.017	0.602	0.029	0.977
real exchange rates t-1	0.163	0.107	1.530	0.129	0.162	0.107	1.520	0.133
China ST interest rate t-1	-1.968	3.953	-0.498	0.620	-1.932	3.963	-0.488	0.627

foreign aggregate GDP	0.655	1.135	0.578	0.565	0.631	1.149	0.549	0.584
foreign inflation	1.798	1.400	1.280	0.202	1.776	1.405	1.260	0.210
foreign real equity price	0.002	0.086	0.021	0.984	0.006	0.086	0.072	0.943
foreign ST interest rates	2.454	2.668	0.920	0.360	2.896	2.595	1.120	0.268
foreign LT interest rates	2.858	6.133	0.466	0.642	3.073	6.153	0.499	0.619
World oil price	-0.073	0.041	-1.800	0.075	-0.074	0.041	-1.810	0.073
ECM term t-1	-0.161	0.056	-2.890	0.005	-0.160	0.056	-2.850	0.005
constant	1.513	0.524	2.890	0.005	1.506	0.527	2.860	0.005
Short run equation for:	**China ST interest rate**							
China real GDP t-1	0.018	0.011	1.710	0.092	0.015	0.013	1.140	0.257
China inflation t-1	-0.055	0.014	-3.860	0.000	-0.051	0.014	-3.650	0.001
real exchange rates t-1	0.002	0.002	0.665	0.508	0.002	0.003	0.675	0.502
China ST interest rate t-1	0.049	0.092	0.530	0.597	0.048	0.093	0.512	0.610
foreign aggregate GDP	0.020	0.026	0.752	0.454	0.020	0.027	0.748	0.456
foreign inflation	-0.025	0.033	-0.769	0.444	-0.024	0.033	-0.742	0.460
foreign real equity price	0.003	0.002	1.590	0.115	0.003	0.002	1.480	0.144
foreign ST interest rates	0.143	0.062	2.300	0.024	0.121	0.061	1.990	0.050
foreign LT interest rates	-0.240	0.143	-1.680	0.097	-0.247	0.144	-1.710	0.090
World oil price	0.000	0.001	-0.262	0.794	0.000	0.001	-0.201	0.841
ECM term t-1	0.008	0.001	6.300	0.000	0.008	0.001	6.180	0.000
constant	-0.077	0.012	-6.350	0.000	-0.077	0.012	-6.220	0.000

Figure 4A-1 Impulse response function: MUC data and DdPS data

a. Impulse response function, MUC data



b. Impulse response function: DdPS data