RESERVE BANK
OF AUSTRALIA

Research Discussion Paper

Seasonal Adjustment of Chinese Economic Statistics

Ivan Roberts and Graham White

RDP 2015-13

The Discussion Paper series is intended to make the results of the current economic research within the Reserve Bank available to other economists. Its aim is to present preliminary results of research so as to encourage discussion and comment. Views expressed in this paper are those of the authors and not necessarily those of the Reserve Bank. Use of any results from this paper should clearly attribute the work to the authors and not to the Reserve Bank of Australia.

Enquiries:

Phone: +61 2 9551 9830
Facsimile: +61 2 9551 8033
Email: rbainfo@rba.gov.au
Website: http://www.rba.gov.au

ISSN 1448-5109 (Online)

Seasonal Adjustment of Chinese Economic Statistics

Ivan Roberts* and Graham White**

RDP 2015-13

November 2015

*Economic Group
**Financial Markets Group
Reserve Bank of Australia

We would like to thank Christopher Kent, John Simon, Alexandra Heath, James Holloway, David Jacobs, Alex Cooper and conference participants at the Chinese Economists Society 2014 China Conference in Guangzhou for helpful comments and suggestions. In preparing this paper we benefited from the insights of earlier internal work undertaken on this topic by Jamie Hall, Ashley Craig, Hao Wang, Adam Cagliarini and Anthony Rush. Naturally, we accept responsibility for any remaining errors. The views expressed in this paper are those of the authors and should not be attributed to the Reserve Bank of Australia.

Authors: robertsi and whiteg at domain rba.gov.au

Media Office: rbainfo@rba.gov.au

Abstract

China's growing importance in the global economy and significance as a source of demand for commodities produced by many countries, including Australia, has focused increasing attention on high-frequency Chinese macroeconomic data. Yet the signal from these data is often distorted by traditional holidays whose timing varies from year to year on the Gregorian calendar. This paper shows that seasonal adjustment procedures (such as the US Census Bureau's X-12-ARIMA and the Bank of Spain's SEATS) can assist in the timely interpretation of a range of commonly used Chinese macroeconomic indicators, including industrial production, trade, credit and inflation. In addition, it suggests a strategy to optimise the selection of moving holiday corrections that account for Chinese New Year, the Dragon Boat festival and the Mid-Autumn festival, prior to seasonal adjustment. It is argued that seasonal adjustment performed with this approach is preferable to simpler techniques.

JEL Classification Numbers: E21, R21, R31

Keywords: seasonal adjustment, moving holidays, calendar effects, China, X-12-ARIMA, SEATS

Table of Contents

Seasonal Adjustment of Chinese Economic Statistics

Ivan Roberts and Graham White

1. Introduction

The growth in importance of China as a driver of global trade flows, and its resilience in the face of slower growth in the advanced economies since the global financial crisis, have led to a much greater degree of attention being focused on monthly and quarterly releases of Chinese macroeconomic statistics. For China's trading partners, such as Australia, rapid or unexpected changes in Chinese data have the ability to move markets, and can lead to revised assessments of domestic economic prospects.

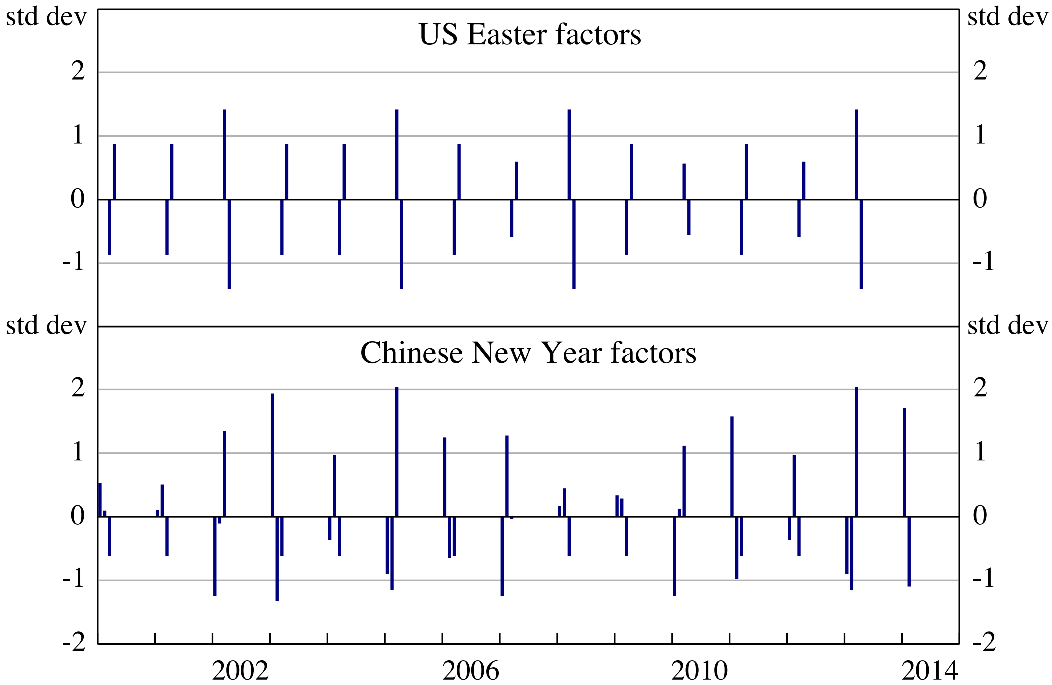
Most monthly and quarterly macroeconomic time series in China are subject to seasonal fluctuations. Agricultural production, for instance, naturally varies with the seasons, giving rise to seasonal movements in food prices (especially for products that are costly to store). Sales of consumer goods tend to spike prior to public holidays, resulting in a strong seasonal pattern in Chinese retail sales. The purpose of seasonal adjustment is to filter, or 'look through', the volatility resulting from the effects of seasonality in original data. Ideally, seasonal adjustment should clarify whether a movement in a given series is larger than would be expected, given knowledge of the regular seasonal pattern for that series. But otherwise regular seasonal patterns in China are often clouded by calendar effects associated with traditional festivals, the timing of which is dictated by the lunar calendar and therefore varies from year to year on the Gregorian calendar.

The timing of Chinese New Year on the Gregorian calendar fluctuates between 21 January and 20 February. This gives rise to distortions in simple computations for assessing the rate of change in Chinese indicators that are widely used in practice, such as year-on-year (year-ended) growth or inflation rates. The reliance on year-on-year growth rates to assess economic conditions is related to the emphasis that has, historically, been placed on these comparisons by China's National Bureau of Statistics (NBS) (Orlik 2011). Until 2011, the NBS did not publish seasonally adjusted data, and at present only a handful of series are available in this form.

The most obvious counterpart of Chinese New Year in Western countries is Easter, which moves between March and April on the Gregorian calendar. Figure 1 compares estimates of Easter holiday factors for the level of the money supply (M2) stock in the United States, and Chinese New Year holiday factors for the same series in the People's Republic of China (see the next section for details), normalised in each case by subtracting the mean and dividing by the standard deviation. Similar to Easter, the effects of the week-long Chinese New Year public holiday vary over time, and give rise to a substantial distortion of economic time series. The magnitude of the effect is apparent from visual inspection of a range of Chinese data, and is consistent with casual observation. Every year, the Chinese New Year holiday receives international attention as the 'world's largest human migration' (Larson 2014), with millions of Chinese citizens travelling home for the holidays. The associated mass movement of people gives rise to noticeable variation in consumption and production patterns across the country. This is easily observable from visual inspection of a typical data series, such as Chinese power generation (Figure 2).

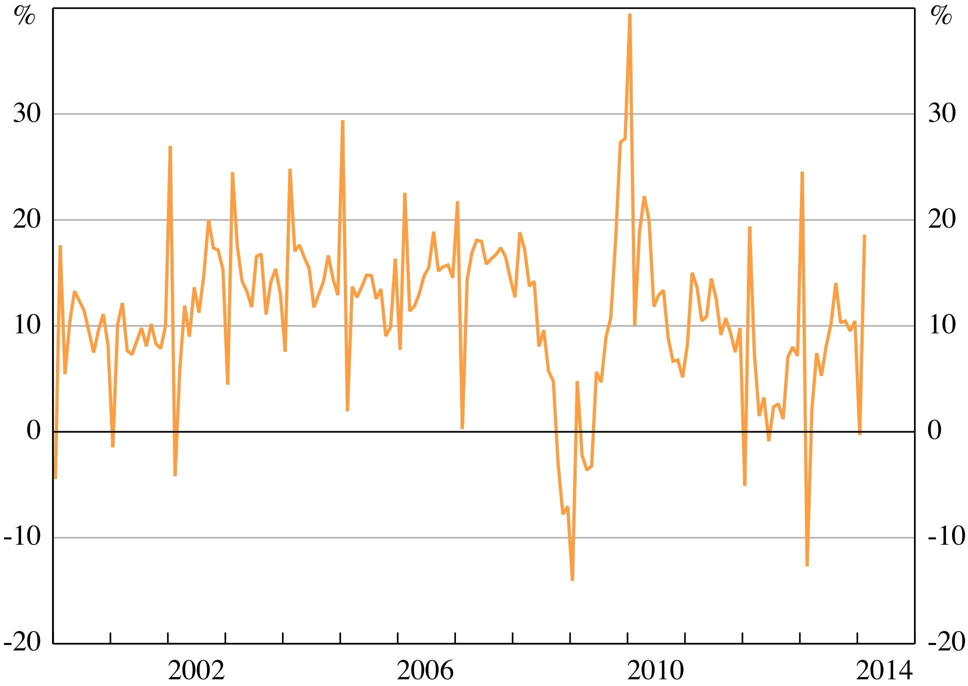
Figure 1: Money Supply Holiday Factors

Normalised



Sources: Authors' calculations; CEIC Data; Federal Reserve Bank of St. Louis

Figure 2: Power Generation
Year-on-year percentage change



Sources: Authors' calculations; CEIC Data

This paper shows that, applied with care and appropriate modifications, seasonal adjustment procedures such as the US Census Bureau's X-12-ARIMA (Findley *et al* 1998) and the Bank of Spain's SEATS (Gómez and Maravall 1996; Maravall 1999) can assist in the timely interpretation of a range of commonly used Chinese macroeconomic indicators. We do not find that any particular seasonal adjustment procedure is dominant. If suitably adapted to the features of Chinese data, both X-12-ARIMA and SEATS can yield seasonal adjustments that compare favourably to simpler approaches.

To account for the effect of moving holidays on Chinese data within the X-12-ARIMA and SEATS frameworks, we use dummy variable corrections, similar to the approach used by Bell and Hillmer (1983) to address the effects of moving festivals such as Easter. Although the use of dummy variable corrections to account for Chinese New Year is not new (Lin and Liu 2003; Shu and Tsang 2005; PBC 2006), we propose a simple extension. Using an historical documentation of public holidays associated with Chinese New Year, we attempt to optimise the selection of these corrections prior to seasonal adjustment. We conjecture that this allows more precise accounting for seasonal patterns than either an *ad hoc* choice of these corrections or the alternative method of simply averaging January and February observations prior to adjustment. Our procedure also extends existing approaches by explicitly taking into account the effects of the two main other, shorter lunar holidays, the Dragon Boat festival (*duanwujie*) in May/June and the Mid-Autumn festival (*zhongqiujie*) in September/October.

After adjusting for holiday effects and applying the above seasonal adjustment procedures, we assess the quality of our adjusted series using standard methods. In addition, we consider the practical performance of seasonally and holiday adjusted data against two simpler, but widely used, techniques: regression on seasonal dummies, and the calculation of year-on-year growth rates as a 'rule of thumb' adjustment for seasonality.

To date, little research has been published on the application of seasonal filters to time series for the People's Republic of China.[1] This paper aims to help fill that gap. Analyses of data from other economies include Lin and Liu (2003), who describe an application of X-12-ARIMA to 10 economic series in Taiwan. Woon (2011) finds that both X-12-ARIMA and SEATS yield 'acceptable' seasonal adjustments of Korean time series in the presence of the traditional holidays such as Seollal (lunar New Year's Day) and Chuseok (Korean Thanksgiving Day). Shuja, Lazim and Wah (2007) use a similar approach to adjust Malaysian data in the presence of moving calendar effects arising from traditional holidays including Islamic observances such as Eid-ul Fitr and Eid-ul Adha, the Hindu festival of Deepavali and Chinese New Year.[2]

Studies that use Chinese data use a range of approaches to correct for seasonality and moving holidays. Some studies choose very simple approaches. For instance, Sun's (2013) analysis of monetary policy shocks in China uses unadjusted industrial production data compiled on a year-on-year growth basis, with prior removal of January observations to mitigate Chinese New Year effects. It is also common to correct for seasonality in the context of an econometric model

1 Exceptions includes Shu and Tsang (2005) and PBC (2006).

2 Liou, Lin and Peng (2012) make use of daily data on monetary aggregates to construct Perng's (1982) bell-shaped holiday variables and feed them into X-12-ARIMA. As we lack comparable daily data for most Chinese economic time series, we are unable to consider this intriguing alternative.

using deterministic dummy variables (e.g. Marquez and Schindler 2007; Garcia-Herrero and Koivu 2009; Zuo and Park 2011; Cheung, Chinn and Qian 2012). However, regression on seasonal dummies can be infeasible in large-scale models (Burman 1980), and is not robust to seasonality that changes over time. Our results suggest that the seasonal pattern in China is likely to be changing over time, which casts doubt on the accuracy of such an approach.

Seasonal adjustment procedures such as X-12-ARIMA have been used in a number of recent studies involving Chinese data.[3] In their factor-augmented VAR study, Fernald, Spiegel and Swanson (2014) use X-12-ARIMA to adjust for seasonality in 29 Chinese economic time series, after removing Chinese New Year effects by averaging January and February observations. Similarly, in their study of the relationship between Chinese and developed economy business cycles, Jia and Sinclair (2013) use quarterly real output data that have been pre-adjusted using X-12-ARIMA. The use of seasonally adjusted Chinese data in current applied work and the growing appetite for adjusted data among Chinese policymakers (revealed by the 2011 decision by the NBS to publish seasonally adjusted figures for key series) provide an additional motivation to investigate the application of seasonal adjustment procedures to Chinese time series.

The paper proceeds as follows. The next section gives an overview of the X-12-ARIMA and SEATS approaches to seasonal adjustment and how they may be adapted in the presence of calendar effects due to Chinese moving holidays. Section 3 describes the data and discusses the results of our seasonal adjustment of 13 selected time series. It compares the results with simpler approaches to smoothing seasonal fluctuations and provides some sensitivity analysis. Section 4 offers brief concluding remarks.

3 The technical literature is divided on the question of whether pre-adjusted data should be used at all in econometric and applied theoretical models, as it can give rise to bias in estimated parameters (Ghysels 1988; Franses 1996; Saijo 2013). Contributions to this literature advise attention to seasonal unit roots and seasonal cointegration. Several recent applications to Chinese data have followed this advice (e.g. Delatte, Fouquau and Holz 2011; Tang, Selvanathan and Selvanathan 2012; Hererias 2013).

2. Seasonal Adjustment with Chinese Moving Holiday Effects

This section gives an overview of the X-12-ARIMA and SEATS (Signal Extraction in ARIMA Time Series) approaches, and how they can be used to adjust data affected by the Chinese New Year and other moving holidays. To implement seasonal adjustment with these approaches we use the X-13-ARIMA-SEATS package, which employs an automatic model selection procedure based on that of the TRAMO (Time Series Regression with ARIMA Noise, Missing Observations and Outliers) program (Gómez and Maravall 1996).

These procedures assume a seasonal decomposition along the following lines:

$$Y_t = T_t \times S_t \times D_t \times H_t \times I_t,$$

where the time series, Y_t, is a multiplicative combination of five unobserved components: trend (or trend-cycle), T_t; seasonal, S_t; trading day, D_t; holiday, H_t; and irregular, I_t. The trading day and holiday components represent calendar effects: trading day effects are related to the number of days and the number of working days in a month, while holiday effects are related to moving holidays such as Chinese New Year. The irregular component is a residual that combines all fluctuations not covered by the other components in the decomposition.[4]

Both the X-12-ARIMA and SEATS procedures first implement a pre-adjustment stage which estimates corrections for Chinese New Year and/or other moving holidays. When the data have been extended in both directions to help mitigate end-point problems, and cleaned of outliers and deterministic calendar effects (Section 2.1), they are fed into a seasonal adjustment procedure (Sections 2.2–2.3) that undertakes the decomposition of the cleaned series into trend, seasonal and irregular components. Finally, the outliers that were removed in the pre-adjustment stage are reintroduced into the seasonal or trend components (depending on the type of outlier), the holiday and trading day components are reincorporated,

4 An additive decomposition may be used as well but the multiplicative version is more common in practice. As observed by Dagum (1976), the multiplicative model will deliver an ineffective seasonal adjustment if the data-generating process of the seasonal component is additive. A multiplicative model is appropriate when the magnitude of the seasonal effect is affected by the level of economy activity. Visual inspection suggests that this is the case for the time series considered in this paper.

and diagnostics can be applied to assess the quality of the seasonal adjustment (Section 2.4)

2.1 'Pre-adjustment' and Correcting for Chinese New Year

The first step of the pre-adjustment is to extend the time series in both directions to reduce end-point problems and minimise revisions. In the process, a selection of dummy variables are used to purge the data of calendar effects. Also in this stage, an outlier detection algorithm is employed to identify and remove outliers.

2.1.1 ARIMA modelling

For the time series of interest, Y_t, define a process

$$y_t = \log Y_t = \beta' \mathbf{X_t} + z_t, \tag{1}$$

where $\mathbf{X_t}$ is a vector of regressors to model calendar-related effects. It includes dummy variables to control for trading day effects, outliers and moving holidays (including Chinese New Year). Because the errors, z_t, are unlikely to be stationary and will most probably be autocorrelated, they are modelled using a zero mean, multiplicative seasonal ARIMA model to allow for the possibility that Y_t is integrated at seasonal lags.

The process for z_t is specified as a seasonal ARIMA $(p, d, q)(P, D, Q)$:

$$\begin{aligned}(1-\delta_1 L^s - \cdots - \delta_P L^{sP})(1-\gamma_1 L - \cdots - \gamma_p L^p)(1-L)^d(1-L^s)^D z_t \\ = (1-\theta_1 L^s - \cdots - \theta_Q L^{sQ})(1-\mu_1 L - \cdots - \mu_q L^q)\varepsilon_t,\end{aligned}$$

where L is a lag operator. For monthly data $s = 12$; for quarterly data $s = 4$; p and q are lag orders of the AR and MA parameters for the non-seasonal ARIMA; P and Q are lag orders of the AR and MA parameters for the seasonal ARIMA; d and D are orders of, respectively, non-seasonal and seasonal integration; and ε_t is a normal, independently and identically distributed random variable.

This expression can be simplified to:

$$\delta(L^s)\gamma(L)(1-L)^d(1-L^s)^D z_t = \theta(L^s)\mu(L)\varepsilon_t.$$

The model can also be expressed as follows:

$$(1-L)^d(1-L^s)^D y_t = \sum_i \beta_i (1-L)^d(1-L^s)^D x_{it} + w_t,$$

where w_t follows a stationary ARMA process.

This model can be estimated by maximum likelihood. The model selection process is automated and done in several stages. Initially, an ARMA model is estimated, and outlier identification and tests for the significance of calendar effects are performed (see Appendix B for details). Next, unit root tests are used to determine the order of differencing. Then, an iterative process is applied to determine the lag order of ARMA parameters. The lag orders of the seasonal part of the ARIMA model are chosen by minimising an information criterion.[5]

A similar procedure is then applied to obtain the lag orders of the non-seasonal part of the ARIMA model. The chosen ARIMA model is then compared with a default ARIMA$(011)(011)$ model; if the chosen model is found to display a lower information criterion than the default model, regressors for calendar effects and tests for outliers are reapplied, and a final model is selected.

2.1.2 Adjusting for the Chinese New Year holiday

Our approach to adjust for Chinese New Year uses the moving holiday regressor of Bell and Hillmer (1983). In its simplest version, this approach defines a dummy variable

$$H(\tau,t) = \frac{\tau_t}{\tau},$$

where t is the month in which part of Chinese New Year falls, τ_t is the number of days affected by Chinese New Year in month t, and τ is the total number of holiday-affected days. The dummy variable is equal to the fraction of holiday-affected days that fall in each month. It has differential quantitative impacts in the months of January and February, depending on the number of days of the holiday that fall in each.

5 Similar to the TRAMO procedure, X-13-ARIMA-SEATS minimises a variant of the Bayesian information criterion.

An alternative three-sub-period version employed by Lin and Liu (2003) takes the form:

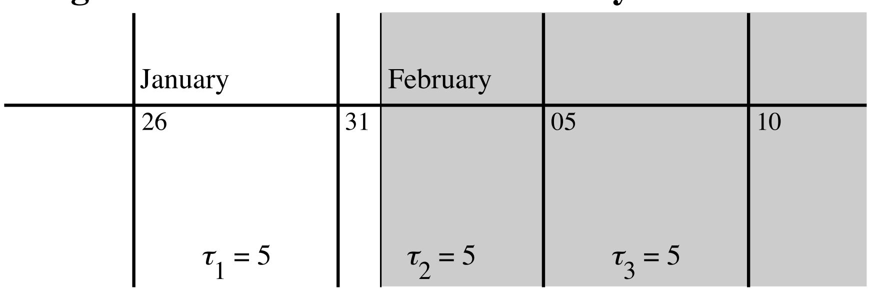
$$H_i(\tau_i, t) = \frac{\tau_{it}}{\tau_i}, i = 1, 2, 3,$$

where *it* is the month in which part *i* of the period affected by Chinese New Year falls, τ_{it} is the number of days affected by part *i* of Chinese New Year in month *t*, and τ_i is the total number of holiday-affected days in part *i* of Chinese New Year. Effectively, the January–February period is partitioned into three sub-periods in which the holiday is assumed to have differential effects: the sub-period leading up to the holiday, the sub-period during the holiday and the sub-period after the holiday. The dummy for each sub-period is equal to the fraction of holiday-affected days in that sub-period that fall in each month.

Figure 3 illustrates how moving holiday regressors can be used to remove the effect of Chinese New Year, based on one particular example. In the figure:

$$H_1(\tau_1, 1) = 1, H_1(\tau_1, 2) = 0;$$
$$H_2(\tau_2, 1) = 0.2, H_1(\tau_2, 2) = 0.8;$$
$$H_3(\tau_3, 1) = 0, H_1(\tau_3, 2) = 1.$$

Figure 3: Chinese New Year Holiday Corrections



Allowing the effect of Chinese New Year to be absorbed by three dummy variables rather than one increases the flexibility with which the effect can be modelled. In the example, the eve of Chinese New Year is assumed to fall on 31 January, and each of the three sub-periods is assumed to have a length of five days. Unfortunately, the literature provides little guidance regarding the length of the sub-periods to which each dummy variable corresponds. Lin and Liu (2003) assume that $\tau_i = \tau$ for each H_i. But there is no reason to assume that the number of days affected by Chinese New Year in each sub-period is the same. In principle, the number of days in each sub-period (τ_1,τ_2,τ_3) can be allowed to vary according to the characteristics of the individual time series.

Lin and Liu (2003) follow the suggestion of Findley and Soukup (2000) that the selection of τ be chosen by finding the model that minimises an Akaike information criterion (AIC), corrected for finite sample sizes – namely, the AICC of Hurvich and Tsai (1989):

$$AICC = \min_{\tau_i} \left\{ -2\mathscr{L}_N(\beta) + 2n_p \left(1 - \frac{n_p+1}{N}\right)^{-1} \right\},$$

where $\mathscr{L}_N(\beta)$ is the maximised log likelihood function with parameters β, evaluated over N observations, and n_p is the number of parameters.[6] The reason for this approach is that the models with different τ are not nested and, therefore, model selection cannot proceed on the basis of standard likelihood ratio tests.

To extend the approach of Lin and Liu (2003), we propose that the lengths of the three sub-periods be optimised for each individual time series. The method is straightforward: for any given series, we estimate a seasonal ARIMA model for each possible combination of sub-period lengths: (2,2,2), (2,2,3), … (2,2,T), …, (2,3,2), … (2,T,2), …, (3,2,2), …, (T,2,2), …, (2,T,T), (3,T,T), … (T,T,T). We impose a maximum sub-period length of T = 20.[7] We then select the combination of window lengths (τ_1^*,τ_2^*,τ_3^*) that minimises the AICC.

2.1.3 Adjusting for additional moving holidays

Once a specification of Chinese New Year adjustments has been decided by the above procedure, we implement a similar approach to adjust for the Dragon Boat

6 The maximised log likelihood is given by

$$\mathscr{L}_N(\beta) = \frac{-N^*}{2}\log(2\pi) - \frac{N^*}{2}\log\sigma^2 - \frac{1}{2\sigma^2}\sum_{s=s^*}^{N}(\log Y_t - \beta'\mathbf{X_t})^2.$$

7 Our experiments suggest that the results do not change substantially with higher T.

(May–June) and Mid-Autumn (September–October) festivals. We define

$$G_j(\phi_j, t) = \frac{\phi_{jt}}{\phi_j}, j = 1, 2, 3,$$

where jt is the month in which part j of the period affected by a given festival falls, ϕ_{jt} is the number of days affected by part j of the holiday in month t, and ϕ_j is the total number of holiday-affected days in part j of the festival. The May–June (or September–October) period is partitioned into three sub-periods such that the dummy for each sub-period is equal to the fraction of holiday-affected days in that sub-period that fall in each month. We apply the same optimisation method as that described above to determine the sub-period lengths. However, as the Dragon Boat and Mid-Autumn festivals usually last for three days, compared with seven days for Chinese New Year, we impose a shorter maximum sub-period length of ten days.

2.1.4 Outlier detection and removal

When an ARIMA model has been estimated, and all moving holiday corrections have been applied, the residuals are used to identify candidate outliers, using a method based on the outlier detection strategy of Chang, Tiao and Chen (1988). Details are provided in Appendix B. When outliers have been identified, the ARIMA model is re-estimated with appropriate dummy variables included in the $\mathbf{X_t}$ vector. This procedure is iterated until no additional outliers are found.

2.2 The X-12 Seasonal Filters

The X-12 procedure is a non-parametric algorithm that iterates between estimates of the trend and seasonal components, using pre-defined filters to smooth seasonal fluctuations from the data. A stylised description of the X-12 filters is given in Appendix B.[8] When the time series has been pre-adjusted (including for Chinese New Year, trading days and outliers, and forecasted and backcasted), the seasonal

8 The X-12 method represents an evolution from various earlier seasonal adjustment techniques developed by the United States Bureau of the Census, including the X-11 method (Shishkin, Young and Musgrave 1967). It has been refined over the years, including through the development of X-11-ARIMA by Statistics Canada in the 1970s (Dagum 1975). Bell and Hillmer (1984) provide an historical overview.

adjustment procedure can be implemented. In the final stage, the trend, seasonal and irregular components are combined with additional deterministic components (including Chinese New Year and trading day effects) removed in the ARIMA modelling stage.

2.3 SEATS

Unlike the X-12-ARIMA procedure, which applies pre-defined filters to the pre-adjusted data from the ARIMA stage, the SEATS procedure conducts a direct signal extraction using the ARIMA model to decompose the data into trend, seasonal and irregular components (see Appendix B). The decomposition assumes that these components are orthogonal, and that no white noise can be extracted from a component that is not the irregular one (Gómez and Maravall 1996). The trend and seasonal components are defined to account for the permanent characteristics of the series – that is, the spectral peaks at the origin and at seasonal frequencies – while the irregular component should be white noise or a low order moving average process (Burman 1980; Pollock 2002).

The SEATS program applies the signal extraction procedure described by Burman (1980), which applies a Wiener-Kolmogorov-type filter to the original series and yields minimum mean square error estimators of the three components. At the final stage, as in the X-12-ARIMA procedure, these three components are modified to reintroduce the deterministic effects removed in the ARIMA modelling step.

2.4 Diagnostic Tests

We use standard diagnostic tests to assess the quality of our seasonal adjustment (see Appendix B for a description). To determine whether moving holiday dummies specified to capture Chinese New Year effects are jointly significant, a chi-squared test is used. For all series, we conduct separate significance tests for Chinese New Year, the Dragon Boat festival and the Mid-Autumn festival respectively. If the dummy variables corresponding to a given moving holiday are insignificant, they are dropped.

Assuming that seasonality is present, assessing the quality of a given seasonal adjustment can be difficult. As noted by Bell and Hillmer (1984), all adjustment procedures involve a degree of arbitrariness in establishing a seasonal decomposition. One widely used criterion is due to Nerlove (1964, p 262), who defines seasonality as 'that characteristic of a time series that gives rise to spectral peaks at seasonal frequencies'. The spectrum may be estimated parametrically by plugging in estimated coefficients from a time series model (see Monsell (2009) for further details). Informal visual inspection of spectral plots can be used to determine if spectral peaks at seasonal frequencies are removed by the various seasonal adjustment procedures.

Another criterion that we consider is the sensitivity of the seasonal adjustment to changes in sample. To do this, we consider robustness to revisions by seasonally adjusting each series over successively increasing time series intervals and averaging absolute percentage revisions for each month, and overall. The percentage revision of the seasonally adjusted series is defined as:

$$R_t = \left| \frac{A_{t|T} - A_{t|t}}{A_{t|t}} \right| ,$$

where $A_{t|n}$ is the seasonal adjustment of the series $y_1, y_2, \ldots, y_n$ for $t \leq n \leq T$, and the final adjustment of observation t is $A_{t|T}$.

'Sliding spans' analysis (Findley *et al* 1990) involves comparing seasonal adjustments for overlapping spans of a given time series. Typically, four overlapping spans are considered. For each month of the calendar year, percentage differences across spans for the seasonally adjusted series and its month-on-month changes are calculated. A range of metrics and rules of thumb have been devised to analyse sliding spans (see Findley *et al* (1990)). In this paper, we focus on the distribution (maximum, minimum and central tendency) of month-on-month changes to help assess the sensitivity of our benchmark seasonal adjustments.

3. Seasonally Adjusting Chinese Economic Time Series

This section discusses the properties of a selection of Chinese economic time series and shows the results of seasonal adjustment using X-12-ARIMA and SEATS.

3.1 Data

We consider one quarterly times series (GDP) and twelve monthly time series: fixed asset investment (FAI), industrial value added ('industrial production'), the consumer price index (CPI), merchandise export values, merchandise import values, credit, total social financing (TSF), money supply (M2), crude steel gross output, rail freight volumes, power generation, and nominal retail sales. These data are all official statistics produced by the NBS, China Customs (exports and imports) or the People's Bank of China (credit, TSF and money supply). Table 1 displays some basic properties of the times series used.[9]

A number of these series were chosen due to the intensive use that is made of them by analysts of Chinese macroeconomic developments (e.g. Batson 2013). Industrial production, FAI, retail sales, trade values, M2, credit and TSF are regularly reported in the press following their monthly releases. Holz (2013) and Fernald, Malkin and Spiegel (2013) find little evidence that Chinese official data are systematically distorted. However, given that many official data series are still viewed with scepticism by analysts, we also consider three less 'high-profile' series – crude steel, rail freight volumes and electricity generation – that are also timely indicators of growth in Chinese economic activity.[10]

9 For additional information on the data used, see Appendix A.

10 Some analysts have considered the 'Li Keqiang Index' (named after China's current premier) as an alternative gauge of economic activity. According to a US State Department memorandum released by WikiLeaks, in 2007 Mr Li Keqiang (then the Chinese Communist Party Secretary of Liaoning province) expressed scepticism about official statistics and noted his personal preference for data on railway cargo volumes, electricity consumption and bank credit (see Fernald *et al* (2013)).

Table 1: Data – Summary

Series	Source[(a)]	Sample	Units	Mean growth per annum[(b)]	Standard deviation[(c)]
FAI	NBS	2000:M1–2014:M2	Values (CNY)	27.7	8.8
Industrial production	NBS	2000:M1–2014:M2	Index	13.4	3.6
CPI	NBS	2000:M1–2014:M2	Index	2.4	2.3
Exports	GAC	2000:M1–2014:M2	Values (USD)	14.6	16.5
Imports	GAC	2000:M1–2014:M2	Values (USD)	16.9	19.5
Credit	PBC	2000:M1–2014:M2	Values (CNY)	16.9	5.2
TSF	PBC	2002:M2–2014:M2	Values (CNY)	20.6	91.2
Money supply	NBS	2000:M1–2014:M2	Values (CNY)	17.1	3.7
Crude steel	NBS	2000:M1–2013:M12	Tonnes	13.8	10.9
Rail freight	NBS	2000:M1–2014:M2	Tonnes	5.8	7.1
Power generation	NBS	2000:M1–2014:M2	Kilowatt hours	9.6	7.7
Retail sales	NBS	2000:M1–2011:M12	Values (CNY)	18.9	4.7
Real GDP	NBS	2000:Q1–2013:Q4	Index	9.9	2.0

Notes: (a) PBC refers to People’s Bank of China, GAC refers to the General Administration of Customs of the People’s Republic of China
(b) Compound geometric annual average of month-on-month percentage changes (quarter-on-quarter for quarterly data)
(c) Standard deviation of year-on-year (year-ended) percentage changes

Sources: Authors’ calculations; CEIC Data

We conduct adjustments for the moving holiday associated with Chinese New Year based on an historical identification of the scheduling of public holidays by government authorities (Table 2). There are currently seven official nationwide public holidays. These are: New Year (1 January), Chinese New Year (three days in January/February), the Qingming festival (4 or 5 April), Labour Day (1 May), the Dragon Boat festival (one day in May/June), the Mid-Autumn festival (one day in September/October) and National Day (1–3 October).

Table 2: Historical Chinese New Year Public Holiday Dates

Year	Date of first day	Public holidays	Additional work days
2000	5 February	4–10 February	11–12 February
2001	24 January	24–23 January	20–21 January
2002	12 February	12–18 February	9–10 February
2003	1 February	1–7 February	8–9 February
2004	22 January	22–28 January	17–18 January
2005	9 February	9–15 February	5–6 February
2006	29 January	29 January–4 February	28 January, 5 February
2007	18 February	18–24 February	17, 25 February
2008	7 February	6–12 February	2–3 February
2009	26 January	25–31 January	24 January, 1 February
2010	14 February	13–19 February	20–21 February
2011	3 February	2–8 February	30 January, 12 February
2012	23 January	22–28 January	21, 29 January
2013	10 February	9–15 February	16–17 February
2014	31 January	31 January–6 February	26 January, 8 February

Sources: Selected government releases and newspaper articles

The scheme of public holidays and working weeks in China has changed over time. The July 1994 Labor Law of the People's Republic of China stipulated a 44 hour working week, although this was shortened in March 1995 when the State Council issued a circular announcing the adoption of a 40 hour (five day) working week. Prior to 2000, a single day was observed as a public holiday for Chinese New Year. This was extended to three days in 2000 following the State Council's revision to the Regulation on National Festival and Commemorative Holidays in September 1999. In practice, from 2000 onwards the government has issued dates for these three days matching traditional dates of the Spring Festival on the Chinese lunar calendar. It has typically issued instructions lengthening the three-day holiday to a seven-day holiday by absorbing adjacent weekdays and requiring a prior, or subsequent, Saturday and Sunday to be treated as working days.

The sample we consider is, in general, 2000:M1–2014:M2 for monthly data and 2000:Q1–2014:Q1 for quarterly data.[11] Although earlier data are available for

11 Owing to breaks in the NBS's provision of monthly data for retail sales after 2011, we only use monthly data up to December 2011 for this series. Similarly, due to a break in early 2014 we use crude steel data up to December 2013.

many series, we start the sample in 2000 due to the significant changes made to public holiday arrangements, which effectively initiated the practice of a week-long public holiday in observance of Chinese New Year. While the effects of Chinese New Year are clearly observable in unadjusted data prior to 2000, the seasonal pattern changes markedly in 2000. We exclude the sample prior to 2000 to prevent this major change in policy towards public holidays contaminating our estimated moving holiday coefficients.

Another, more minor, policy-driven change is also worth noting. In 2008, the Labour Day holiday was shortened from a three-day holiday (which was typically expanded to seven) to a one-day holiday. In place of the longer holiday, the traditional Dragon Boat, Qingming and Mid-Autumn festivals were all listed as one-day official public holidays. As with Chinese New Year, the Dragon Boat and Mid-Autumn festivals move between months on the Gregorian calendar. Also similar to Chinese New Year, these one-day holidays are usually extended to three days.[12]

In this analysis, we control for the effect of Chinese New Year, the Dragon Boat festival and the Mid-Autumn festival. Although the more recent, and shorter, moving holidays associated with the two smaller festivals have a smaller potential impact on economic activity, their importance cannot be ruled out *ex ante*.[13]

Finally, it is worth noting that our ability to make explicit adjustments for Chinese New Year is constrained by how the raw economic data are released. Industrial production and FAI figures are not released separately for January and February. Rather, a total figure for the two months is released at the same time as the February release for other statistics. As it is not possible to identify the value or volume of activity in each month separately, for these two series we assign the average monthly flow to each of the two months prior to seasonal adjustment.

12 If adjacent to a weekend a long weekend is observed; if not, a three-day holiday is mandated with one or two weekend days converted to working days to ensure a continuous three-day break from work.

13 In practice, the Mid-Autumn festival coincides with the week-long National Day holiday in October around once every three years. When it does coincide, the authorities typically lengthen the National Day holiday by one day.

3.2 Results

We use the X-13-ARIMA-SEATS program to conduct ARIMA modelling and seasonal adjustment, and the Genhol utility developed by Brian C Monsell to construct moving holiday regressors.[14] Table 3 summarises the results of ARIMA modelling for both X-12 and SEATS, and diagnostic tests for the presence of seasonality after the data have been adjusted. We refer to estimates obtained using these models as our 'benchmark' seasonal adjustment estimates. Figures for a number of these series are included for reference in Appendix C.

Table 3: Seasonality Diagnostics and ARIMA Specifications

Series	Seasonality detected	F_S	F_M	ARIMA model chosen	SEATS ARIMA model used
FAI	Yes	173.7***	1.5	(0 1 1)(1 1 0)	Same
Industrial production	Yes	80.0***	8.8**	(0 1 1)(0 1 0)	Same
CPI[(a)]	Yes	125.3***	3.5*	(3 1 0)(0 1 1)	Same
Exports[(a)]	Yes	106.9***	0.5	(0 1 1)(0 1 1)	Same
Imports[(b)]	Yes	63.6***	1.5	(0 1 0)(0 1 1)	Same
Credit[(c)]	Yes	29.1***	3.9**	(1 1 2)(1 0 1)	Same
TSF[(a)]	Yes	52.0***	3.3**	(1 1 1)(0 1 1)	Same
Money supply[(d)]	Yes	31.1***	2.6**	(0 1 0)(0 1 1)	Same
Crude steel	Yes	11.1***	4.8**	(0 1 0)(0 1 1)	Same
Rail freight[(a)]	Yes	35.1***	1.4	(0 1 0)(0 1 1)	Same
Power generation[(a)]	Yes	267.4***	1.9*	(0 1 1)(0 1 1)	Same
Retail sales[(a)]	Yes	263.9***	5.5**	(0 1 0)(0 1 1)	(0 1 1)(0 1 1)
Real GDP	Yes	55 630.1***	3.2**	(0 1 1)(0 1 0)	Same

Notes: ***, ** and * represent significance at the 0.1, 1 and 5 per cent levels, respectively
(a) Adjusted for Chinese New Year
(b) Adjusted for Chinese New Year, the Dragon Boat festival and Mid-Autumn festival
(c) Adjusted for Chinese New Year and the Dragon Boat festival
(d) Adjusted for Chinese New Year and the Mid-Autumn festival

For all series an F-test for the presence of a seasonal pattern (F_S) finds evidence of seasonality. Significant evidence of moving seasonality (F_M) is also found for

14 These programs are available at <https://www.census.gov/srd/www/x13as/> and <https://www.census.gov/srd/www/genhol/>. The algorithm for optimising the sub-period lengths for moving holiday regressors described in Section 3 executes the X13-ARIMA-SEATS and Genhol programs iteratively until the AICC is minimised and the selection of a seasonal ARIMA model with optimised moving holiday corrections is completed.

many series.[15] The ARIMA models chosen by the automatic model selection procedure for use in SEATS are largely the same as those to which X-12 filters are applied. With the exception of the X-12-ARIMA adjustment for FAI, visual analysis of spectral plots reveals no evidence of residual seasonality. We consider the case of FAI later.

Table 4 displays the estimation results for our moving holiday corrections. As noted earlier, due to data constraints we are unable to correct for Chinese New Year effects in the case of FAI and industrial production. Corrections for the Dragon Boat and Mid-Autumn holidays were also found to be insignificant for these series. GDP was not corrected for moving holiday effects as the Chinese New Year holiday always falls within the March quarter. Similarly, there was no evidence of significant moving holiday corrections for crude steel production.

Table 4: Moving Holiday Diagnostics and Specifications

Series	Chinese New Year effect detected (p-value)	Dragon Boat festival effect detected (p-value)	Mid-Autumn festival effect detected (p-value)
CPI	Yes (0.00)	No (0.77)	No (0.40)
Exports	Yes (0.00)	No (0.43)	No (0.58)
Imports	Yes (0.00)	Yes (0.02)	Yes (0.02)
Credit	Yes (0.03)	Yes (0.00)	No (0.90)
TSF	Yes (0.00)	No (0.31)	No (0.58)
Money supply	Yes (0.00)	No (0.39)	Yes (0.03)
Rail freight	Yes (0.00)	No (0.59)	No (0.86)
Power generation	Yes (0.00)	No (0.12)	No (0.27)
Retail sales	Yes (0.00)	No (0.98)	No (0.82)

With these exceptions, Chinese New Year was found to be significant in all cases. A significant effect of the Dragon Boat festival was found for imports and credit, and the Mid-Autumn festival was significant for imports and money supply.[16] The

15 These tests are described in Appendix B, and are available for X-12-ARIMA output. Lothian and Morry's (1978) combined F-test for identifiable seasonality, which is reported as 'M7' by the X-12-ARIMA package output, also fails to reject the null hypothesis for most series, with the exception of crude steel which is found to be borderline. The results of such tests should be viewed with caution, as Lytras, Feldpausch and Bell (2007) have found that their power is typically quite low.

16 The only series for which all three moving holidays were found to be significant was imports. While statistically significant, the Mid-Autumn festival dummies for this series were too small to be economically significant.

fact that not all holidays were statistically significant for all series suggests that different time series are affected by the various moving holidays to greater or lesser extents. This warns against a ‘one-size-fits-all’ approach to correcting for moving holidays in Chinese data.

Table 5 focuses more specifically on the results for our Chinese New Year moving holiday corrections.[17] A couple of observations can be made about the Chinese New Year corrections chosen by our benchmark procedure. First, the sub-period lengths found by the procedure tend to be relatively long, with most being longer than ten days. A consequence is that the data for March are often also affected by the Chinese New Year holiday when it falls late in February.

Table 5: Chinese New Year Diagnostics and Specifications

Series	**Chinese New Year effect detected**	**Chi-square (p-value)**	**Sub-period 1**	**Sub-period 2**	**Sub-period 3**
			Number of days		
CPI	Yes	153.8 (0.00)	6	5	8
Exports	Yes	132.7 (0.00)	11	19	20
Imports	Yes	235.5 (0.00)	12	6	20
Credit	Yes	8.9 (0.00)	3	17	18
TSF	Yes	34.9 (0.00)	19	20	15
Money supply	Yes	13.3 (0.01)	11	20	3
Rail freight	Yes	23.7 (0.00)	13	20	8
Power generation	Yes	656.0 (0.00)	12	5	17
Retail sales	Yes	73.5 (0.00)	10	16	3

A second observation is that the benchmark sub-period lengths vary considerably across different time series. This suggests that there may be a benefit in allowing each of the three sub-periods to vary for different time series, rather than choosing a length in *ad hoc* fashion that applies to all three intervals. However, there is some evidence that applying sub-period lengths that are shorter than preferred by our procedure can give an adjustment that appears inadequate upon visual inspection, whereas the results are not usually substantially changed by applying sub-period lengths that are longer.

Figures 4 and 5 show sensitivity results for exports and power generation. In each case, applying sub-periods shorter than preferred by our procedure increases

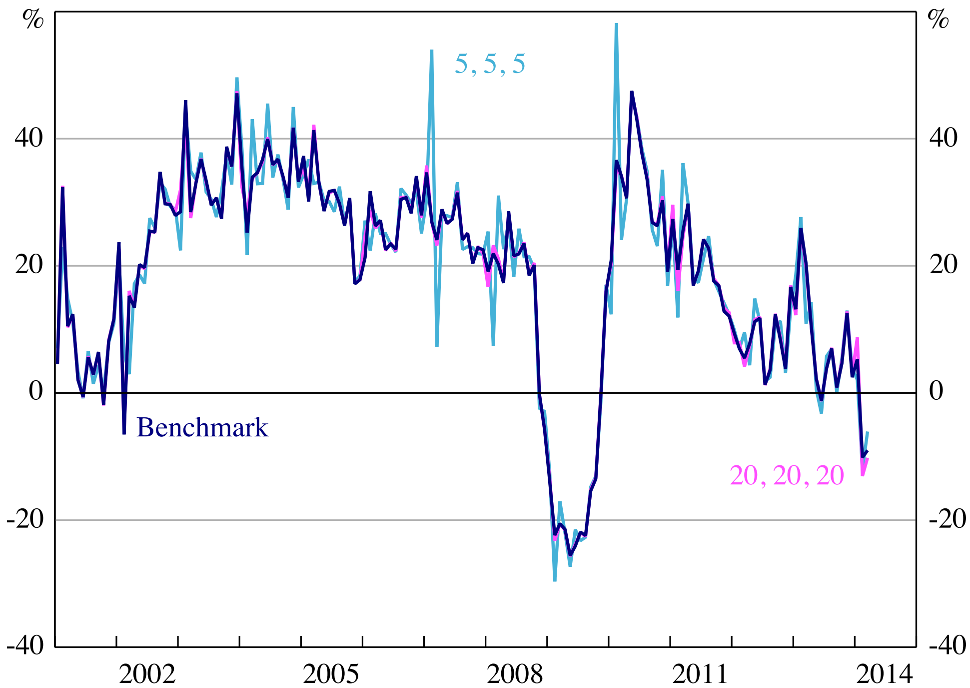
17 Similar results are available for other moving holiday corrections but are omitted for brevity.

the volatility of the year-on-year growth rates noticeably around Chinese New Year. For exports, applying longer sub-period lengths makes little difference to the results. But in the case of power generation, longer sub-periods also result in sharp movements in year-on-year growth rates around Chinese New Year. Given that the sub-periods chosen by our procedure vary noticeably across the indicators we have selected, it seems unlikely that a uniform set of sub-periods – that is, $\tau_i = \tau$, as suggested in earlier literature – will adjust for Chinese New Year adequately across all series.

As our procedure requires some computation, it is worth comparing these results to those of simpler approaches. One of the most widely reported methods of assessing momentum in Chinese economic data is to use the year-on-year percentage change. Computing year-on-year percentage changes is a simple way of attempting to abstract from seasonal effects. However, when a moving holiday is present there are typically very sharp movements in the year-on-year growth rate during the months in which the holiday can occur.

Figure 4: Exports

Year-on-year percentage change, seasonally adjusted

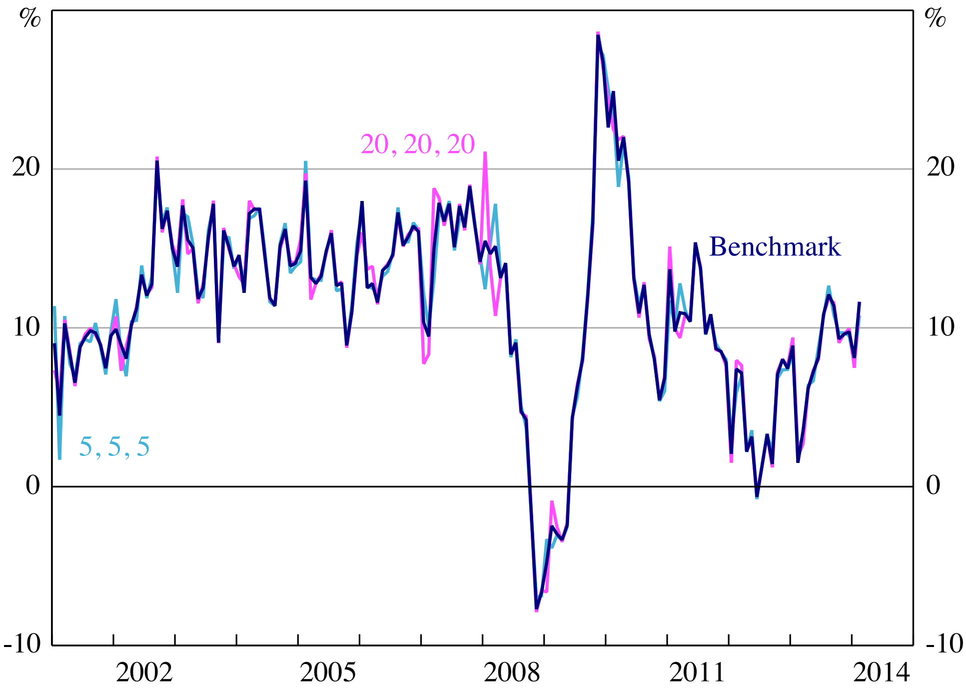


Notes: 'Benchmark' refers to X-12-ARIMA seasonally adjusted estimates using holiday factors as specified in Tables 4 and 5; '5, 5, 5' and '20, 20, 20' refer to estimates in which sub-period lengths for Chinese New Year are set uniformly to 5 days or 20 days, respectively

Sources: Authors' calculations; CEIC Data

Figure 5: Power Generation

Year-on-year percentage change, seasonally adjusted



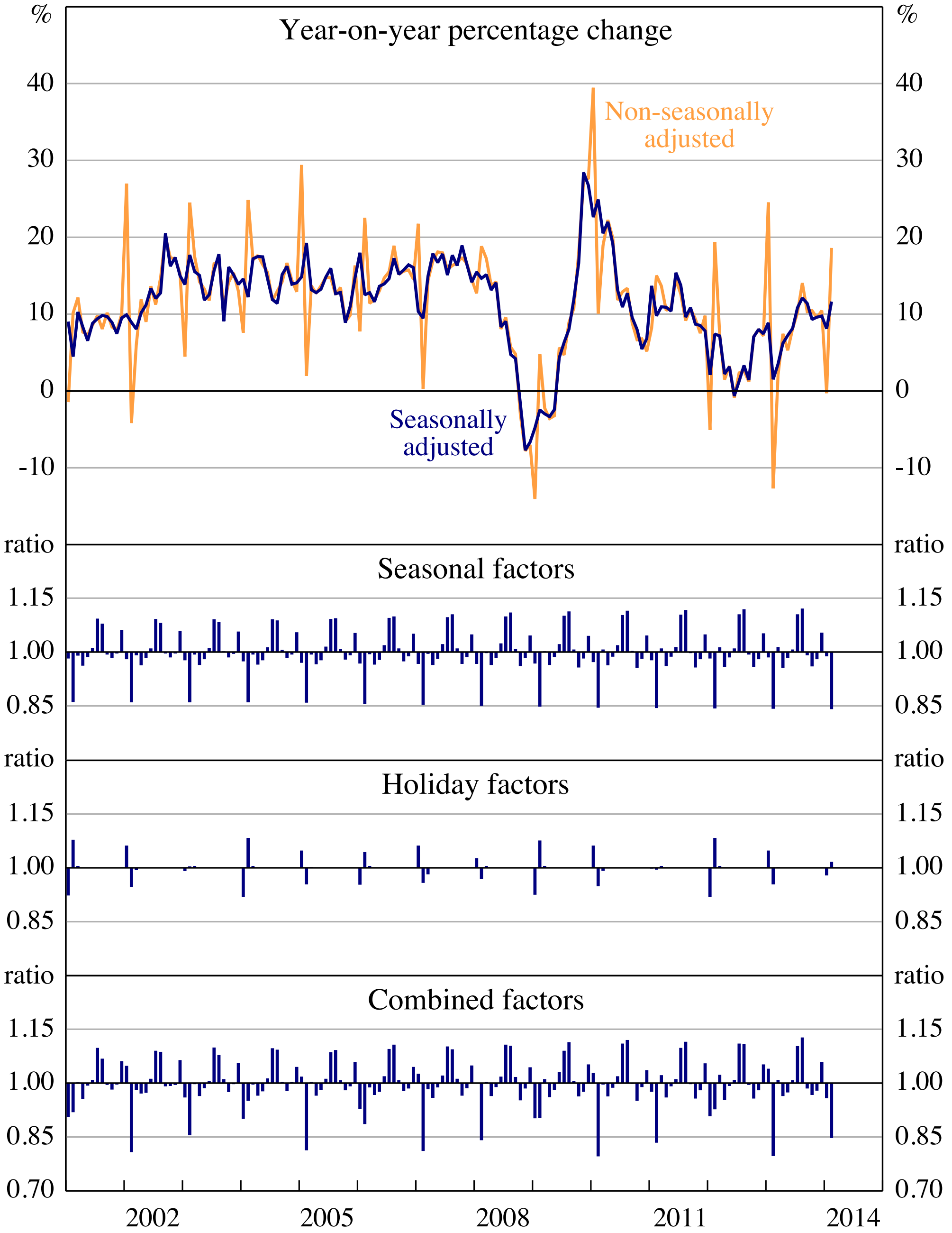
Notes: 'Benchmark' refers to X-12-ARIMA seasonally adjusted estimates using holiday factors as specified in Tables 4 and 5; '5, 5, 5' and '20, 20, 20' refer to estimates in which sub-period lengths for Chinese New Year are set uniformly to 5 days or 20 days, respectively

Sources: Authors' calculations; CEIC Data

A good example is power generation. Since many factories and offices close down over the Chinese New Year holiday period, electricity generation typically declines. If Chinese New Year occurs in January one year and in February the following year, then year-on-year growth in power generation tends to spike sharply higher in January of the second year and sharply lower in February. This effect can be seen in the non-seasonally adjusted line in Figure 6. An observer would obtain little information about the momentum in Chinese power generation around the time of Chinese New Year using this approach.

The influence of Chinese New Year can clearly be seen in the seasonal decomposition of the power generation series produced by X-12-ARIMA (Figure 6). Power generation has a fairly predictable seasonal pattern (second panel of Figure 6), abstracting from Chinese New Year. Incorporating Chinese New Year, the pattern is noticeably less regular (bottom panel of Figure 6).

Figure 6: Power Generation



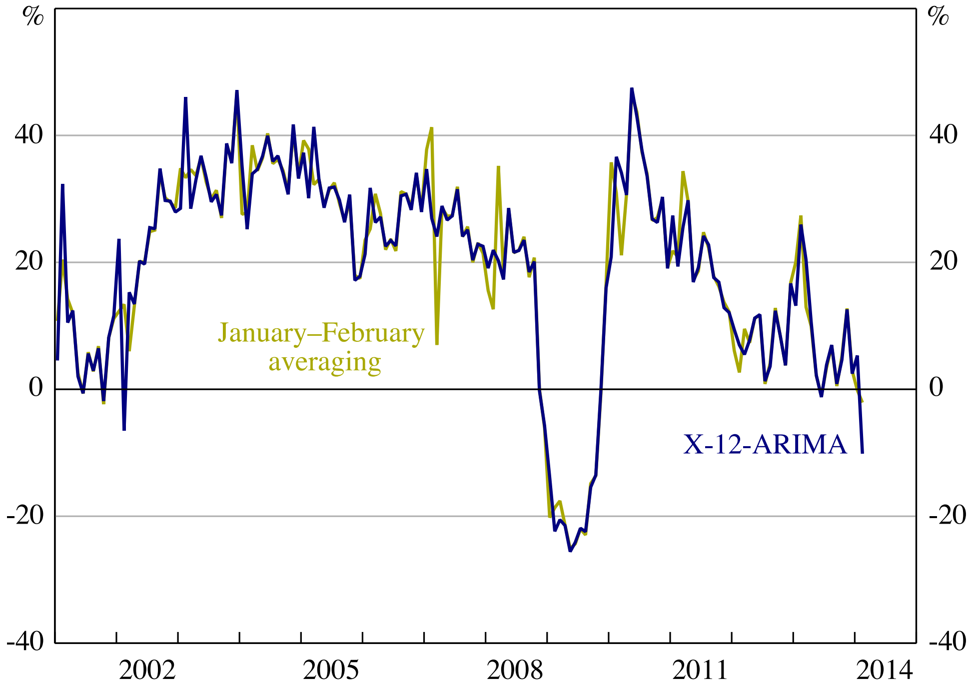
Sources: Authors' calculations; CEIC Data

Another simple method of abstracting from Chinese New Year is to average the values for January and February. By construction, this method will remove the Chinese New Year effect from these months at the cost of also removing some dynamic variation from the series. Moreover, this method gives less timely information than alternative approaches, since a reading on momentum in a given series cannot be obtained until the February data are released. A further potential problem with this approach is suggested by the results in Table 5. Because the effect of Chinese New Year spills over into March, January–February averaging prior to regular seasonal adjustment of the series may not account adequately for such spillovers.

The result of not accounting for a spillover of the moving holiday effect into March can be considered using the example of Chinese exports (Figure 7). The optimised sub-period lengths for the exports series are 11, 19 and 20 days for the periods before, during and after Chinese New Year. This pattern implies that the seasonal adjustment procedure will make a moving holiday correction for March. January–February averaging, however, makes no such adjustment, increasing the volatility of the adjusted series in some periods. For example, in 2007 (when the Chinese New Year holiday began on 18 February) a sharp drop can be seen in the year-on-year growth rate of the January–February averaged series in the month of March.

Figure 7: Exports

Year-on-year percentage change, seasonally adjusted

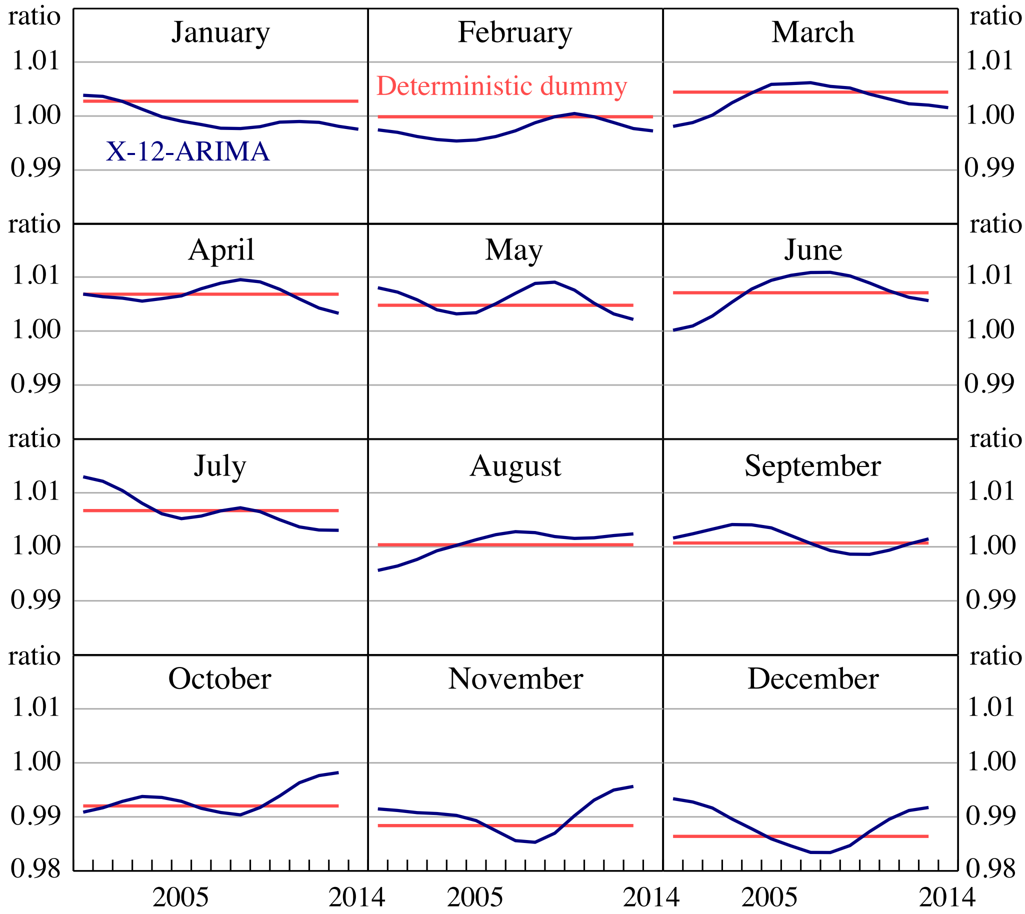


Sources: Authors' calculations; CEIC Data

A general alternative to seasonal adjustment procedures such as X-12-ARIMA and SEATS is to regress the log of the original times series on deterministic monthly seasonal dummies. An advantage of this approach is its simplicity and transparency. The approach is widely used in the academic literature on China (e.g. Marquez and Schindler 2007; Cheung *et al* 2012). Figure 8 illustrates the results of this approach for the credit series. To ensure comparability with the X-12-ARIMA estimates, we incorporate the same Chinese New Year dummies in the estimation as specified in Table 5.

Figure 8: Credit

Seasonal factors



Sources: Authors' calculations; CEIC Data

It is apparent from Figure 8 that the seasonal factors given by X-12-ARIMA can change noticeably over the sample, compared with the static factors produced by the deterministic dummy variable approach.[18] For example, seasonal factors that scale bank credit have varied significantly over time. In a rapidly changing developing economy, such as China, it appears inappropriate to assume that seasonal factors are constant.

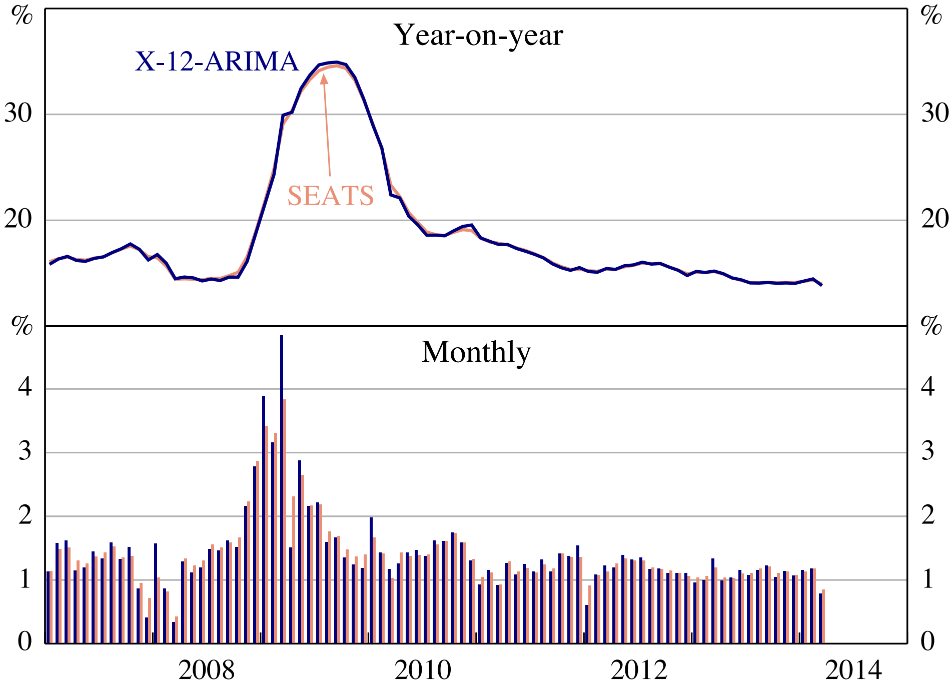
18 The results of *F*-tests reported in Table 3 and additional figures in Appendix C provide evidence of moving seasonality for several other series.

3.3 X-12-ARIMA Versus SEATS

Our results suggest that neither SEATS nor X-12-ARIMA consistently outperforms the other. This is similar to the findings of previous work (Scott, Tiller and Chow 2007). For most indicators we consider, there is little difference: for example, the adjusted credit series is very similar outside of periods of great volatility in credit such as 2009 (Figure 9). Spectral plots generally suggest that both X-12-ARIMA and SEATS do an adequate job of seasonal adjustment, as suggested by the example of power generation (Figure 10). In both cases, peaks in the spectral density at the seasonal frequencies (highlighted by vertical lines in the figure) are eliminated by seasonal adjustment.[19]

Figure 9: Credit Growth

Seasonally adjusted

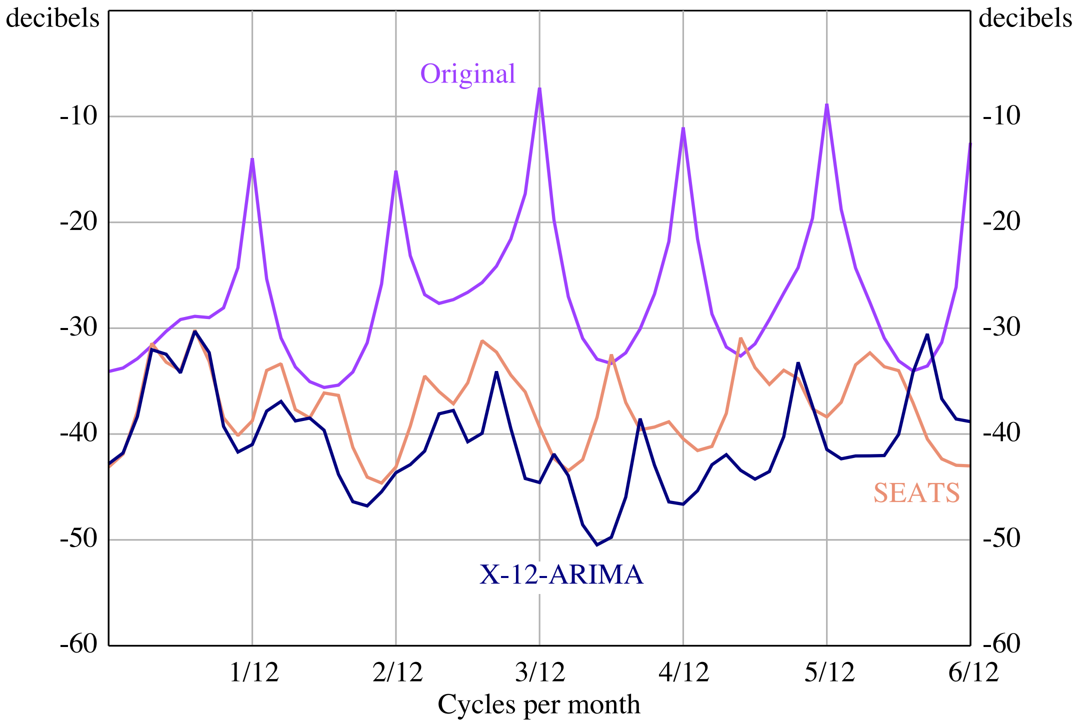


Sources: Authors' calculations; CEIC Data

19 For spectral plots shown in this paper, we use estimated autoregressive spectral densities, following the advice of Findley *et al* (1998). The spectrum depicted in Figure 10 is reported in decibel ($10\log_{10}$) units on the vertical axis to compress the scale of the diagram for easy inspection. Frequencies 1/12 to 6/12 are shown on the horizontal axis. Intuitively, if an event occurs every six months, we would expect to see one-sixth of the cycle every month, and spikes at the 1/6 and 1/12 frequencies in the original data.

Figure 10: Power Generation

Spectral plot



Sources: Authors' calculations; CEIC Data

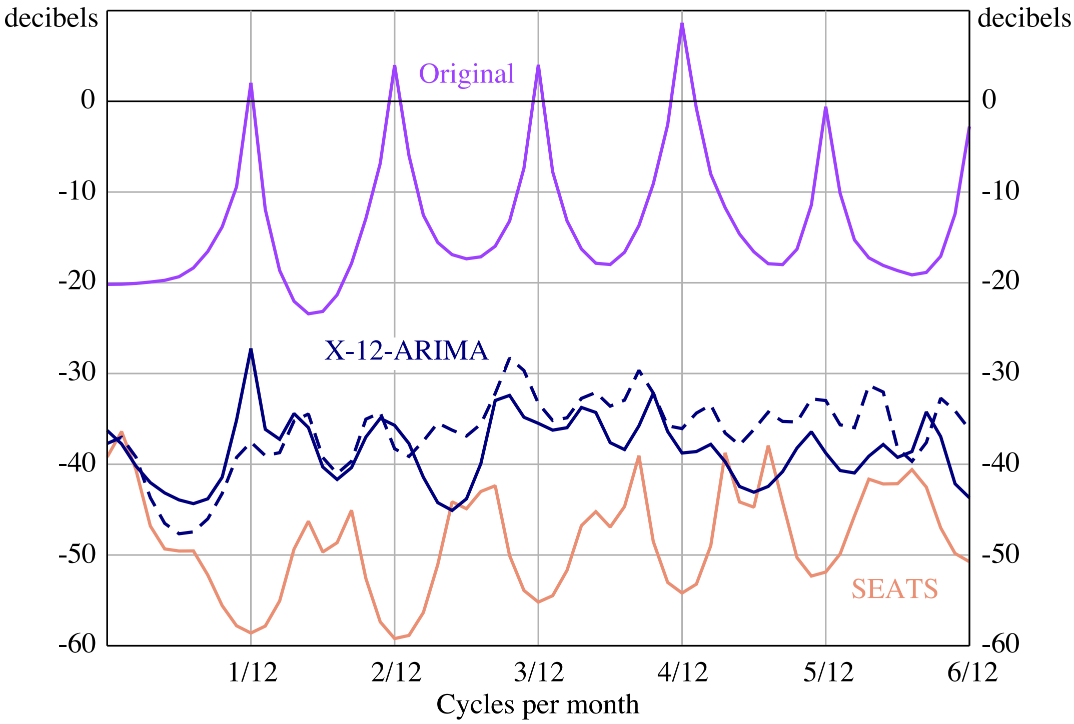
Visual inspection of the other time series we consider suggests that only FAI and industrial production yield significant differences between the estimates produced by X-12-ARIMA and those produced by SEATS. These differences can be clearly seen in plots of the spectrum for FAI (Figure 11). It is apparent that the X-12 filter-based method is not adequately adjusting for seasonal effects, since there is a peak in the spectral plot of the seasonally adjusted series at one of the monthly seasonal frequencies (namely, the 1/12 cycles per month frequency). By comparison, the SEATS adjustment does not show any evidence of residual seasonality.

The better performance of SEATS for this series probably reflects the greater flexibility that SEATS has in selecting appropriate filters for seasonal adjustment. The seasonal decompositions of FAI provided by the two procedures indicate that SEATS estimates a much smoother trend than X-12-ARIMA.[20] Consequently, the seasonal factors are smoother under X-12-ARIMA. For both approaches, the December seasonal factor has become smaller over time (that is, closer to 1.0), with X-12-ARIMA estimating a smoother decline (Figure 12). But using a

20 This point was originally suggested to us by Hao Wang.

Figure 11: Fixed Asset Investment

Spectral plot

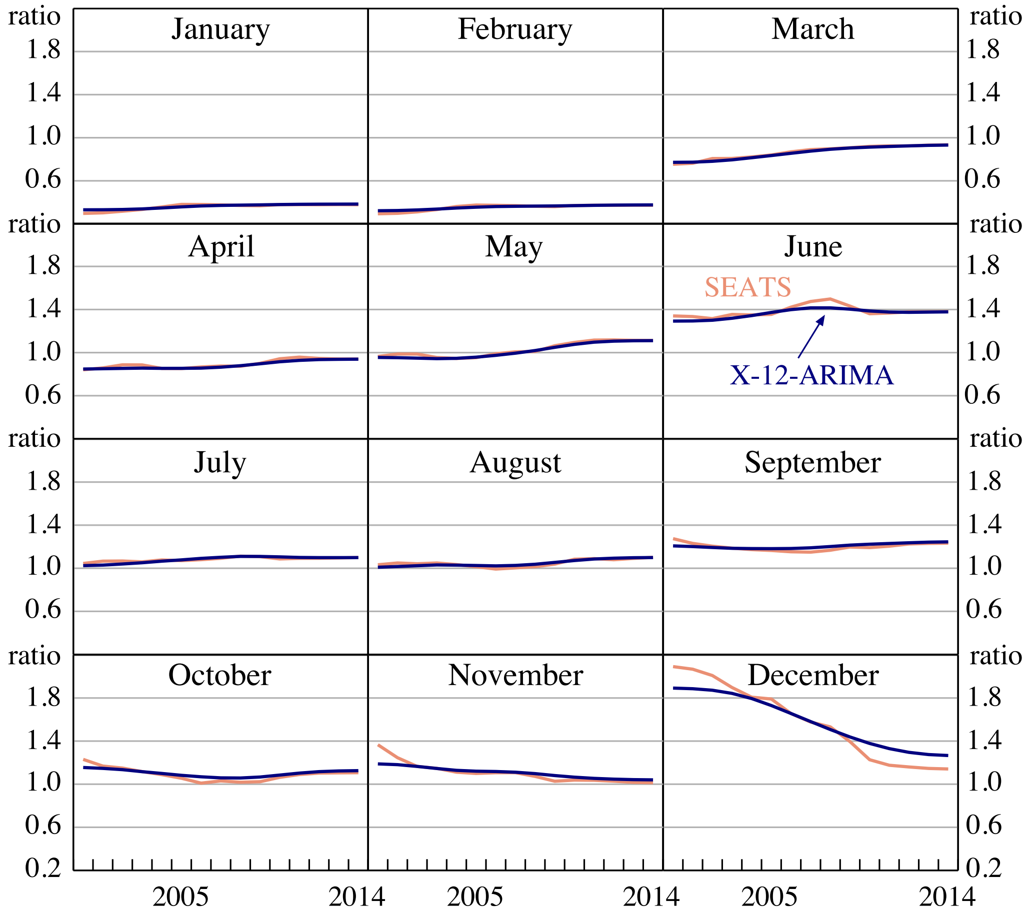


Note: Dashed series uses a 33-period Henderson trend in the adjustment procedure
Sources: Authors' calculations; CEIC Data

much smoother Henderson trend in the X-12 procedure (for example, a 33-period Henderson trend) allows X-12-ARIMA to estimate trend and seasonal components that are closer to those produced by SEATS, and greatly reduces the size of the seasonal peak in the spectral plot (see the dashed line in Figure 11). These results suggest that, for some series, the additional flexibility of the SEATS filter allows it to provide a better seasonal adjustment than the default filters used by X-12-ARIMA.

Figure 12: Fixed Asset Investment

Seasonal factors



Sources: Authors' calculations; CEIC Data

3.4 An Alternative Specification of Chinese New Year Corrections

Our benchmark approach to correcting for Chinese New Year allows the sub-period lengths (τ_1, τ_2, τ_3) to be determined entirely by the data. A potential criticism of this approach is that we do not use all available information about Chinese public holidays. In particular, we identify the start of the second sub-period using the official start date for the Chinese New Year public holiday, but allow the length of the middle sub-period to be data-determined rather than incorporating the official end date of the public holiday into our calculations.

An alternative way of specifying the Chinese New Year holiday corrections is to fix the middle sub-period (τ_2) for all series to a certain number of days, and allow the other two sub-periods (τ_1 and τ_3) to be decided with reference to the AICC. As the public holiday involves a total break from work of seven days, we set $\tau_2 = 7$.[21]

Table 6 shows the effect on the sub-period lengths chosen by our procedure. For the series considered, constraining the middle sub-period to seven days tends to result in longer 'before' and 'after' sub-periods than would otherwise be the case (compare Table 5).

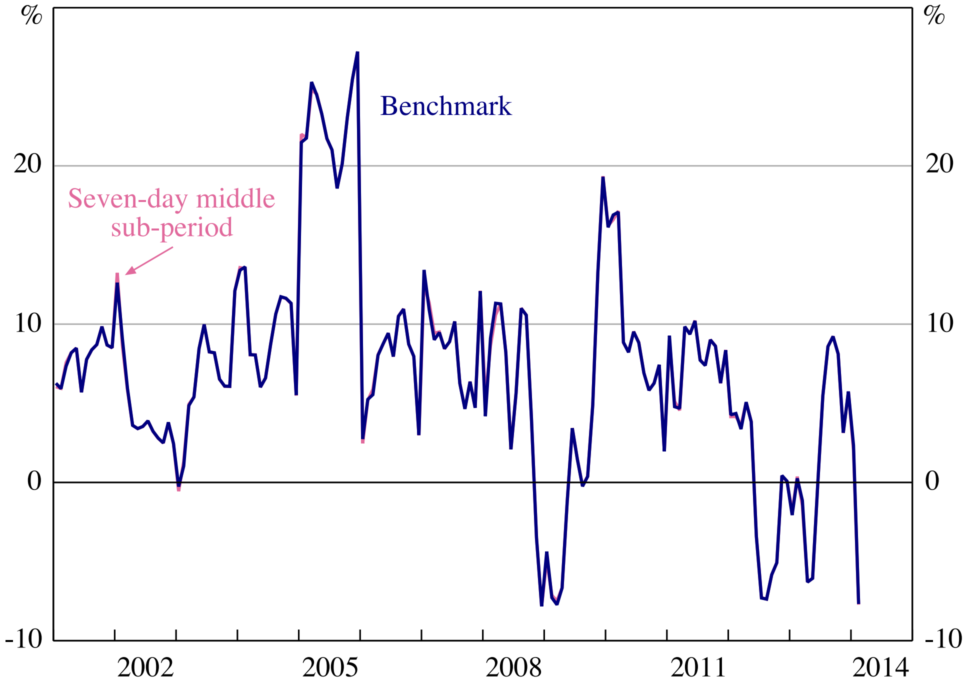
Table 6: Chinese New Year Specifications – Fixed Middle Sub-period

Series	**Chinese New Year effect detected**	**Chi-square (p-value)**	**Sub-period 1**	**Sub-period 2**	**Sub-period 3**
			Number of days		
CPI	Yes	156.49 (0.00)	7	7	11
Exports	Yes	125.48 (0.00)	10	7	14
Imports	Yes	189.22 (0.00)	7	7	3
TSF	Yes	19.17 (0.00)	19	7	20
Money supply	Yes	9.43 (0.02)	19	7	5
Rail freight	Yes	30.11 (0.00)	18	7	20
Power generation	Yes	512.40 (0.00)	12	7	16
Retail sales	Yes	62.36 (0.00)	11	7	20

Fixing the middle sub-period affects all series differently, but usually has a limited effect on the overall seasonal adjustment. Figures 13 and 14 compare the results of the constrained holiday moving corrections to those of our benchmark approach for the rail freight and export series. For rail freight, and some other series, there is little discernible difference between the two approaches. For exports, the effect of fixing the middle sub-period can occasionally be seen around January–February. As there is no obvious criterion for choosing between the two approaches, we focus on the benchmark seasonally adjusted estimates.

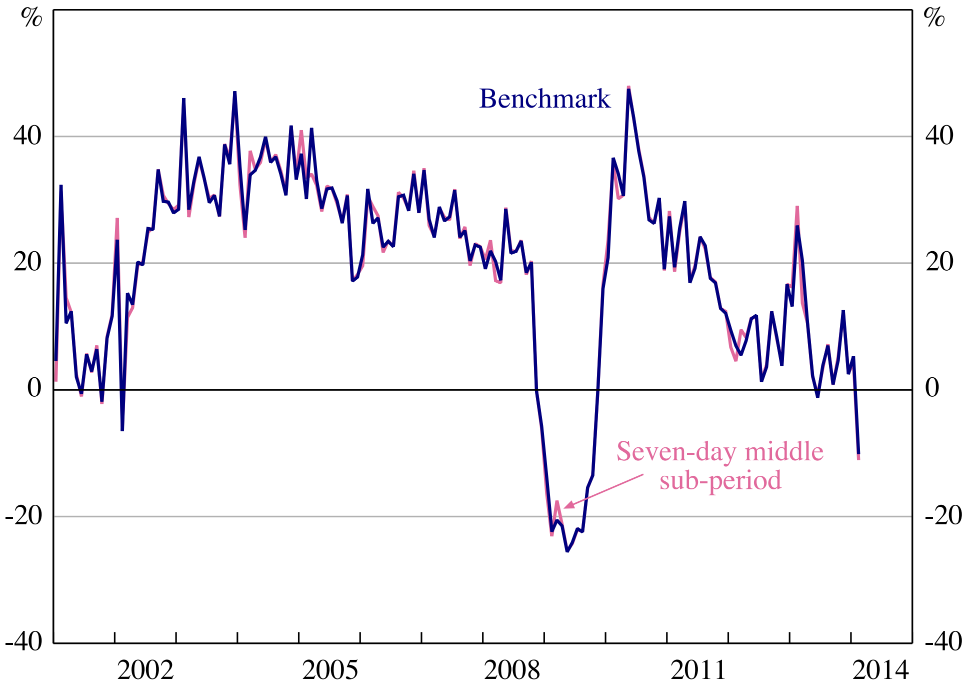
21 In their application of the Lin and Liu (2003) Chinese New Year corrections, PBC (2006, p 391) propose the dummy variable specification ($\tau_1 = 20, \tau_2 = 7, \tau_3 = 20$).

Figure 13: Rail Freight
Year-on-year percentage change, seasonally adjusted



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure
Sources: Authors' calculations; CEIC Data

Figure 14: Exports
Year-on-year percentage change, seasonally adjusted



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure
Sources: Authors' calculations; CEIC Data

3.5 Sensitivity Analysis

We consider the sensitivity of our benchmark seasonal adjustment to changes in sample with the aid of revision histories and sliding spans. The seasonal adjustment is more robust for some series than for others. The time series for which revisions are most noticeable are FAI, exports, imports and crude steel (Table 7). Interestingly, the X-12-ARIMA adjustment for FAI seems particularly prone to revision. This may reflect a poor seasonal adjustment for this series, consistent with the evidence from spectral plots.

Table 7: Average Absolute Revisions of the Seasonal Adjustment
Per cent

Series	X-12-ARIMA	SEATS
FAI	2.59	1.04
Industrial production	0.47	0.60
CPI	0.10	0.08
Exports	1.50	1.48
Imports	1.86	1.73
Credit	0.25	0.28
TSF	0.13	0.10
Money supply	0.21	0.17
Crude steel	1.40	1.16
Rail freight	0.86	0.79
Power generation	0.62	0.59
Retail sales	0.41	0.47
Real GDP	0.13	0.24

Sliding spans analysis yields similar results. For each indicator, month-on-month changes in the seasonally adjusted series are compared over four overlapping spans (quarter-on-quarter changes are considered in the case of GDP). Table 8 shows the distribution of differences across spans. The seasonal adjustment for the trade, rail freight and crude steel data are least stable, while FAI does not stand out on this metric.

Table 8: Differences in Month-on-month Changes across Spans
Based on X-12-ARIMA estimates, per cent

Series	Span length	Minimum	Median	Maximum	Standard deviation
FAI	86	0.00	0.25	1.77	0.37
Industrial production	86	0.01	0.36	2.12	0.53
CPI	98	0.00	0.08	0.26	0.12
Exports	99	0.02	1.09	3.31	1.61
Imports	99	0.02	1.22	3.29	1.81
Credit	102	0.01	0.11	0.65	0.17
TSF	98	0.01	0.13	0.45	0.19
Money supply	102	0.00	0.16	0.66	0.24
Crude steel	84	0.02	0.76	5.61	1.13
Rail freight	98	0.01	0.89	5.86	1.32
Power generation	98	0.03	0.51	2.54	0.75
Retail sales	84	0.03	0.45	1.84	0.67
Real GDP[(a)]	29	0.04	0.10	0.48	0.15

Note: (a) Differences in quarter-on-quarter changes across spans

4. Concluding Remarks

The strong growth of the Chinese economy over recent decades has led to an increasing degree of attention being paid to monthly and quarterly releases of Chinese economic data. For China's trading partners, such as Australia, high-frequency movements in Chinese data may have implications for exchanges rates, stock markets and the real economy (for example, through the effect of Chinese domestic growth on its demand for imported commodities).

This paper argues that seasonal adjustment procedures (such as X-12-ARIMA and SEATS) can be helpful in interpreting Chinese data in real time. Unlike simpler methods often used in studies of the Chinese economy, such as regressing the time series on fixed seasonal dummies, these methods allow for the possibility that seasonality is time-varying. Changing seasonality may be important in transition economies such as China, where the evolution of macroeconomic aggregates is subject to rapid structural change.

The paper also proposes strategies to control for moving holidays such as Chinese New Year, the Dragon Boat festival and the Mid-Autumn festival. It generalises the approach of Lin and Liu (2003) by suggesting a simple procedure to optimise the selection of moving holiday regressors, and extending the method to moving holidays other than Chinese New Year. This procedure uses an information criterion to select an 'optimal' choice of moving holiday regressors from a large number of possible alternatives. The paper considers two variants of the procedure that utilise information regarding historical public holiday dates in China differently. Seasonal adjustment using these approaches yields results that compare favourably with rule-of-thumb techniques such as January–February averaging or the computation of year-on-year growth rates. In particular, it is found that the potential of Chinese New Year effects to spill over into the month of March reduces the reliability of simpler approaches.

Appendix A: Data

All of the time series used in this paper are derived from official data. In most cases the monthly time series data are directly implied by published figures, but in some cases we have modified the original data to allow seasonal adjustment to be performed on a levels series at a monthly or quarterly frequency. The modifications we have made to the original data prior to seasonal adjustment are described below.

Fixed asset investment: as implied by monthly year-to-date flows, nominal original currency terms.

Industrial production: index of real value-added industrial production, derived from published year-on-year and year-to-date growth rates. Year-on-year growth rates are used to grow the index for all months except January/February where the year-to-date growth rate for February has been used. The series is initialised in 1994 using an interpolated monthly profile.

Consumer price index: as implied by published monthly percentage changes.

Merchandise export values: as published, US dollar values, 'free on board' basis.

Merchandise import values: as published, US dollar values, 'cost, insurance and freight' basis.

Credit: total stock of bank loans, break-adjusted using published flows and backcast using published year-on-year growth rates prior to June 2004, original currency terms.

Total social financing: total stock of total social financing (TSF), derived by adding the break-adjusted stock of bank loans to an estimated stock of non-bank TSF. Non-bank TSF comprises entrusted loans, trust loans, undiscounted bank accepted bills, net corporate bond issuance and non-financial enterprise equity issuance. Stocks of each component of non-bank TSF are cumulations of published flows, benchmarked to published annual stocks. Original currency terms.

Money supply: M2, as published, original currency terms.

Crude steel gross output: as published, original units (tonnes).

Rail freight volumes: as published, original physical units (tonnes).

Power generation: as published, original physical units (kilowatt hours).

Retail sales: as published, nominal, original currency terms.

Gross domestic product: constant price index, derived from published quarterly year-on-year and year-to-date growth rates. Year-on-year growth rates are used to grow the index. The series is initialised in the four quarters ending in the September quarter of 1999 using arbitrary starting values. The starting values are then iterated numerically until the discrepancy between calculated and published year-to-date growth rates is minimised.

Appendix B: Outlier Corrections, Seasonal Filters and Diagnostic Tests

This appendix provides additional details on correcting for outliers in X-12-ARIMA, a general description of the X-12 and SEATS filters, and details of diagnostic tests used in the procedure.

B.1 Outlier Detection and Removal

In the X-13-ARIMA-SEATS package, a method based on the outlier detection strategy of Chang *et al* (1988) is used to correct for outliers.[22] Typically three types of outliers are defined:

$$AO_t^{t_0} = \begin{cases} 1, t = t_0 \\ 0, t \neq t_0 \end{cases}$$

$$LS_t^{t_0} = \begin{cases} 1, t < t_0 \\ 0, t \geq t_0 \end{cases}$$

$$TC_t^{t_0} = \begin{cases} 1, t < t_0 \\ \alpha^{t-t_0}, t \geq t_0, \text{ where } 0 < \alpha < 1, \end{cases}$$

where additive outliers (*AO*) alter the level of the series temporarily for one period only; level shifts (*LS*) shift the level permanently; and trend corrections (*TC*) shift the level at a point in time and have a decaying effect thereafter.

Outliers falling into these categories are defined by calculating test statistics for each time point and outlier type (given constant AR and MA parameters). These are compared to a table of critical values. When outliers have been identified, the ARIMA model is re-estimated with appropriate dummy variables included in the $\mathbf{X_t}$ vector. This procedure is iterated until no additional outliers are found. In the final stage of the seasonal adjustment procedure, additive outliers are reincorporated into the seasonal component, while level shifts and trend corrections are reincorporated into the trend component of the series.

22 It is important to correct for moving holidays *prior* to outlier detection. Otherwise, for example, the January and February observations in Chinese time series will typically be marked as outliers due to the outsized impact of Chinese New Year.

B.2 The X-12 Seasonal Filters

Define the fitted values of Equation (1), which exclude the trading day (D_t) and holiday (H_t) components of a series, as:[23]

$$\hat{Z}_t = \log \hat{Y}_t.$$

The trend is initially estimated using a 2×12 moving average (which preserves linear trends and eliminates order-12 constant seasonalities)[24]

$$T_t^{(1)} = M_0(\hat{Z}_t),$$

which is then used to calculate the detrended series (often called the 'SI ratio')

$$(S_t + I_t)^{(1)} = \hat{Z}_t - T_t^{(1)}.$$

The first iteration of the seasonal component is then estimated as a 3×3 moving average (which preserves linear trends), over each monthly observation of the combined seasonal and irregular components[25]

$$S_t^{(1)} = M_1 \left[(S_t + I_t)^{(1)} \right].$$

This series is normalised to $\hat{S}_t^{(1)}$ so that the sum of seasonal factors over a 12-month period is approximately zero.

The first estimate of the seasonally adjusted series is:

$$A_t^{(1)} = \hat{Z}_t - \hat{S}_t^{(1)}.$$

23 This description of the X-12 filters is largely derived from the comprehensive exposition of the X-11 method by Ladiray and Quenneville (2001).

24 The so-called 2×12 moving average has coefficients $\frac{1}{24}\{1,2,2,2,2,2,2,2,2,2,2,2,1\}$.

25 The 3×3 moving average has coefficients $\frac{1}{9}\{1,2,3,2,1\}$.

In the next stage of the algorithm, a second estimate of the trend is formed by applying a Henderson moving average[26] to the initial estimate of the seasonally adjusted series:

$$T_t^{(2)} = H_1\left(A_t^{(1)}\right).$$

The second iteration of the seasonal-irregular component is then given by:

$$(S_t + I_t)^{(2)} = \hat{Z}_t - T_t^{(2)}.$$

The seasonal component is estimated using a 3×5 moving average over each month (which preserves linear trends):[27]

$$S_t^{(2)} = M_2\left[(S_t + I_t)^{(2)}\right].$$

Finally, the seasonal factors are normalised again, resulting in another estimate of the seasonally adjusted series:

$$A_t^{(2)} = \hat{Z}_t - \hat{S}_t^{(2)}.$$

The entire procedure is then iterated two more times with minor variations.[28]

B.3 The SEATS Seasonal Filter

In broad terms, seasonal adjustment in SEATS is undertaken as follows. We can rewrite Equation (1) as:

$$\phi(L)z_t = \phi_S(L)\phi_T(L)z_t = \theta(L)\varepsilon_t,$$

26 The purpose of applying a Henderson moving average is to improve the smoothness of the trend and preserve a locally polynomial trend of degree 2^3.

27 The 3×5 moving average has coefficients $\frac{1}{15}\{1,2,3,3,3,2,1\}$.

28 The above description incorporates a slight modification of the actual X-12 procedure. In addition to the outlier detection techniques used in the ARIMA step, the X-12 algorithm has its own automated 'extreme value' detection, which is applied repeatedly in successive iterations of the procedure. Essentially, the extreme value detection procedure applies error bands around the irregular component and down-weights observations that fall within a certain number of standard deviations of the mean. This effectively smooths the series further. Our own experiments replicating X-12-ARIMA for Chinese data suggest that the seasonal adjustment of Chinese time series is little changed if this feature is 'turned off' by setting the tolerance limits for extreme value detection to very high numerical values.

where $\phi_S(L)$ contains the seasonal autoregressive factors and $\phi_T(L)$ contains the non-seasonal factors.

The population spectrum of the ARIMA$(p,d,q)(P,D,Q)$ will take the general form:

$$f(\omega) = \frac{\sigma_\varepsilon^2 \theta(e^{i\omega})\theta(e^{-i\omega})}{2\pi\phi(e^{i\omega})\phi(e^{-i\omega})},$$

where $\omega \in [0,\pi]$.

Under certain assumptions (see Pollock (2002)), the autocovariance generating function for the ARIMA model can be decomposed into three components corresponding to the trend, seasonal and irregular. The estimated ARIMA model provides a way of parameterising the spectrum of the time series, so that a (pseudo) spectral decomposition can be achieved:

$$f(\omega) = f(\omega)_T + f(\omega)_S + f(\omega)_R,$$

where $f(\omega)_T$, $f(\omega)_S$ and $f(\omega)_R$ refer to the trend, seasonal and irregular components.

B.4 Diagnostic Tests

The test statistics used in this paper are all relatively standard in seasonal adjustment analysis.[29] The first is a test of whether the monthly (or quarterly) means of the detrended series (that is, the SI ratio) are equal. It tests the hypothesis that there is no seasonality:

$$\begin{aligned} &H_0 : m_1 = m_2 = \cdots = m_k \\ &H_1 : m_p = m_q \text{ for at least one pair } (p,q). \end{aligned}$$

Assuming that the values of the seasonal factors are independently distributed as normal with means m_i and a common standard deviation, one test statistic is:

$$F_S = \frac{S_A^2/(k-1)}{S_R^2/(n-k)},$$

29 Simulations by Lytras *et al* (2007) suggest that the power of these tests is highly variable across different ARIMA models, and in some cases rather low.

which follows an F-distribution with $k-1$ and $n-k$ degrees of freedom (Ladiray and Quenneville 2001, pp 57, 135). This test is based on a one-way analysis of variance, where S^2 (the total sum of squares) is decomposed into S_A^2, the variance of the averages due to seasonality, and S_R^2, the residual variance.

A second test aims to determine the presence or otherwise of moving seasonality through a two-way analysis of variance. Variation in the detrended series is decomposed into inter-month, inter-year and residual components:

$$S^2 = S_M^2 + S_Y^2 + S_r^2,$$

where S^2 is the total sum of squares, S_M^2 is the inter-month sum of squares, S_Y^2 is the inter-year sum of squares and S_r^2 is the residual sum of squares. An F-test is used to test the null hypothesis that there is no change in seasonality across the complete years of the sample:

$$F_M = \frac{S_Y^2/(N-1)}{S_r^2/(N-1)(k-1)},$$

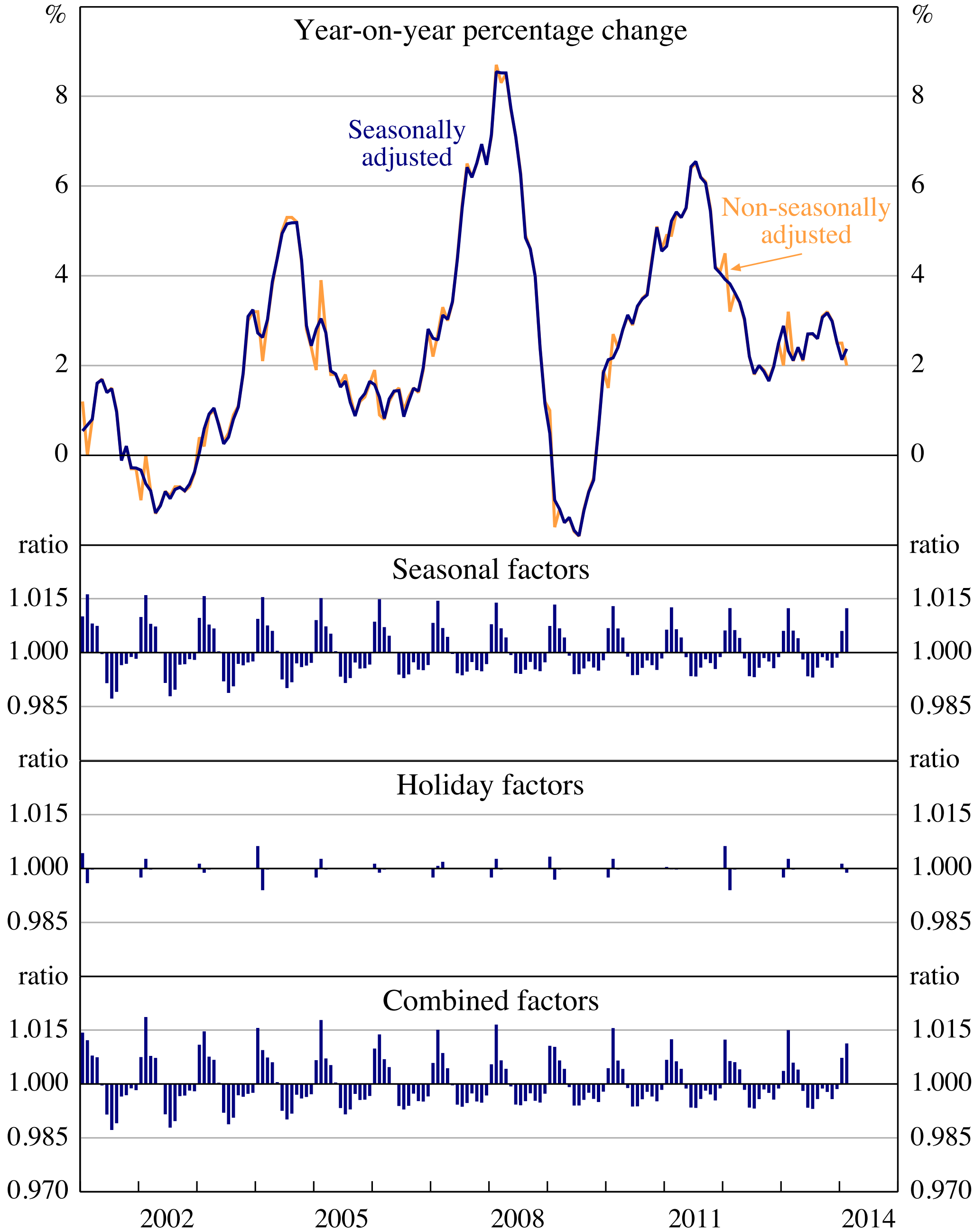
where N is the total number of years, and F_M follows an F-distribution with $(N-1)$ and $(k-1)(N-1)$ degrees of freedom.[30]

30 A test statistic reported by X-12-ARIMA ('M7') that combines the two F-tests is a test for the presence of 'identifiable seasonality' attributable to Lothian and Morry (1978):

$$T = \frac{1}{2}\left(\frac{7}{F_S} + \frac{3F_M}{F_S}\right)^{\frac{1}{2}}.$$

Appendix C: Additional Figures

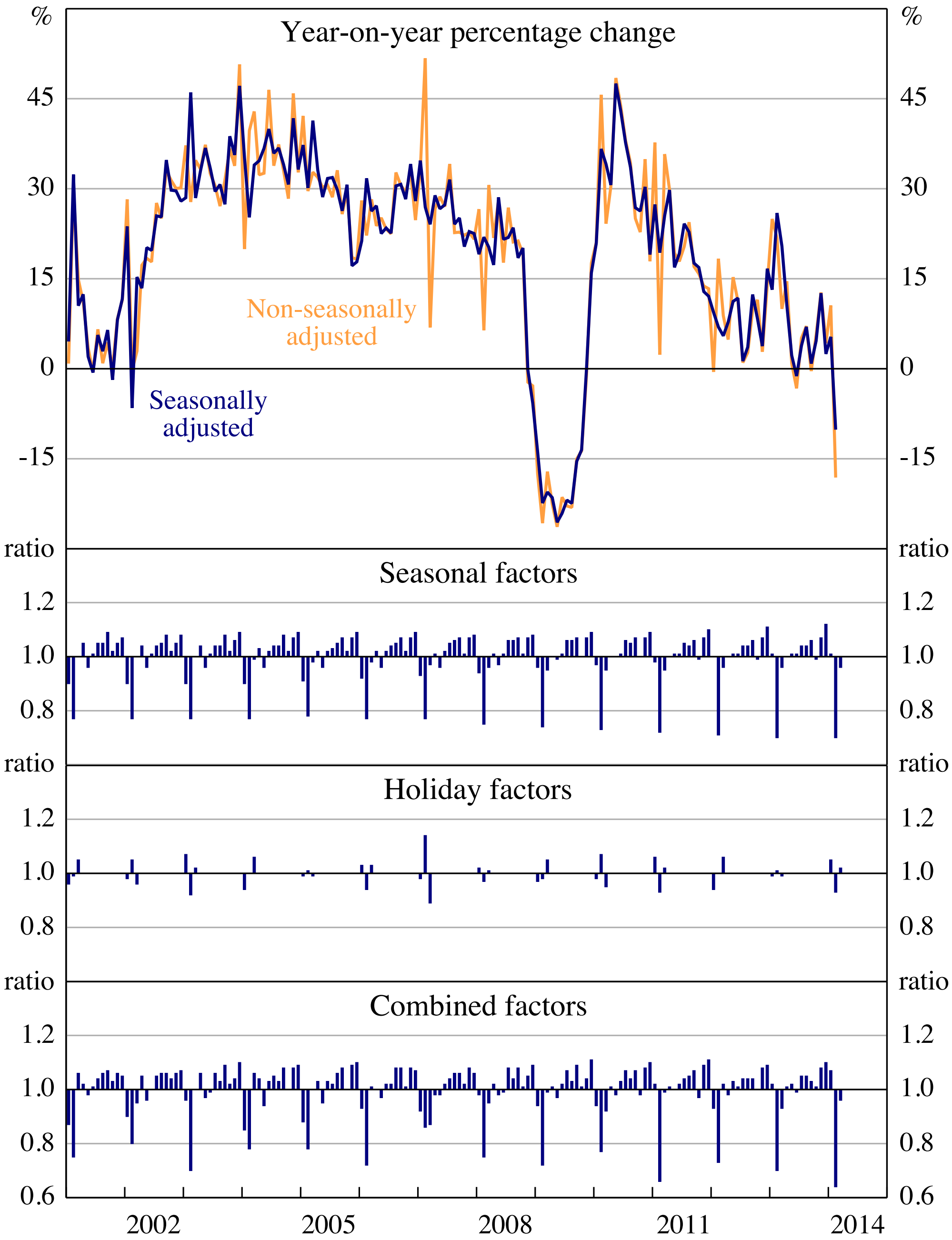
Figure C1: Consumer Price Index



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure

Sources: Authors' calculations; CEIC Data

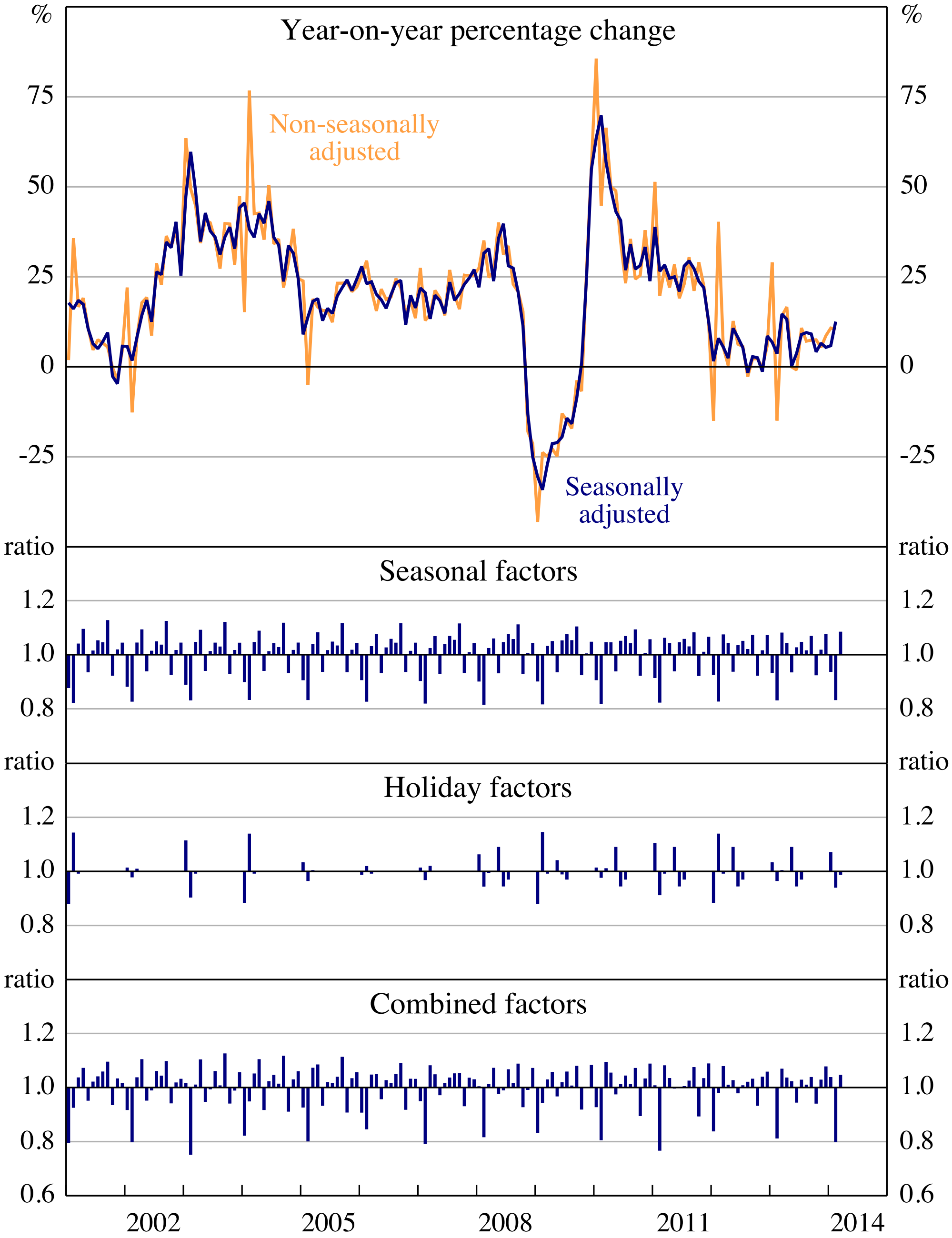
Figure C2: Exports



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure

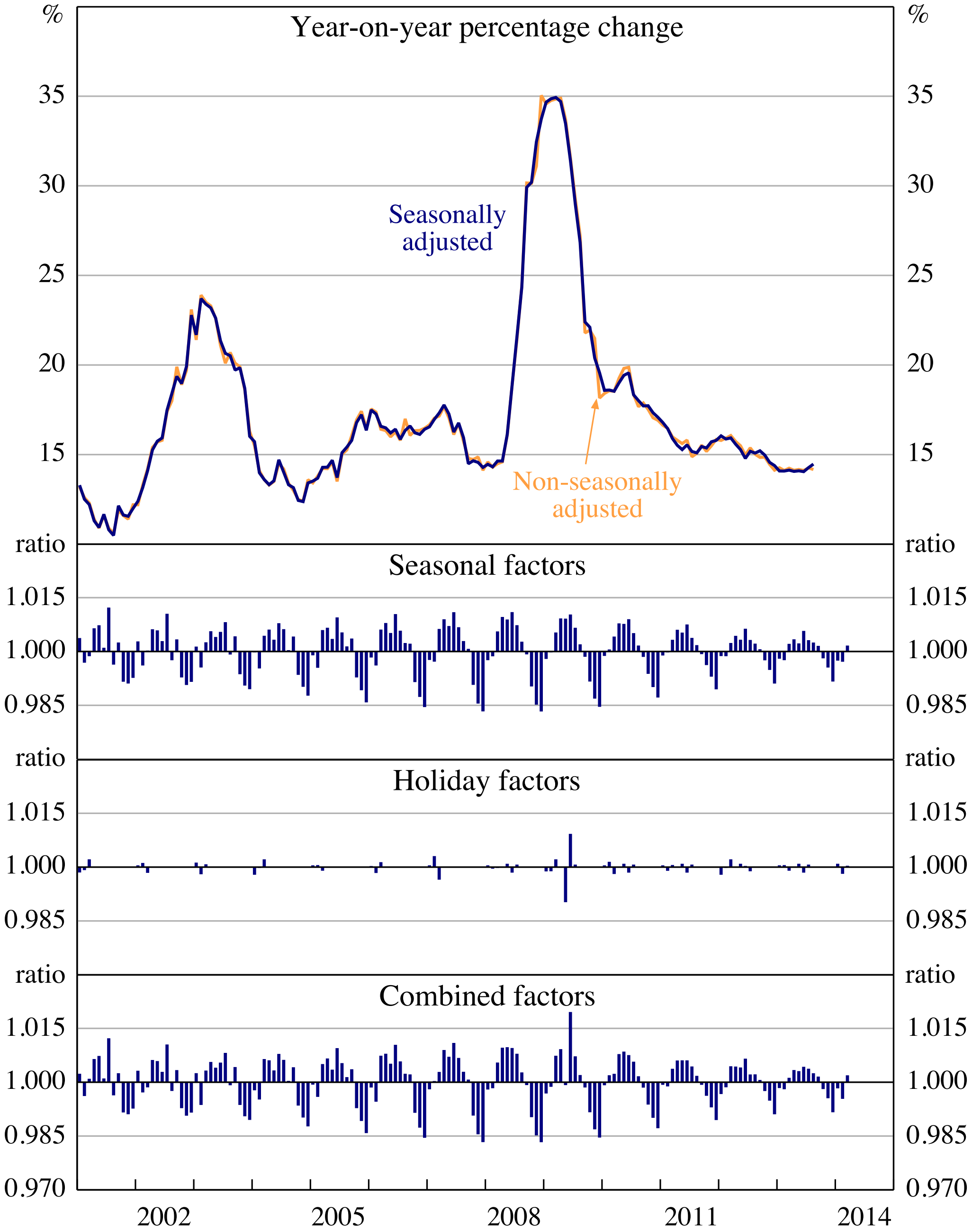
Sources: Authors' calculations; CEIC Data

Figure C3: Imports



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure
Sources: Authors' calculations; CEIC Data

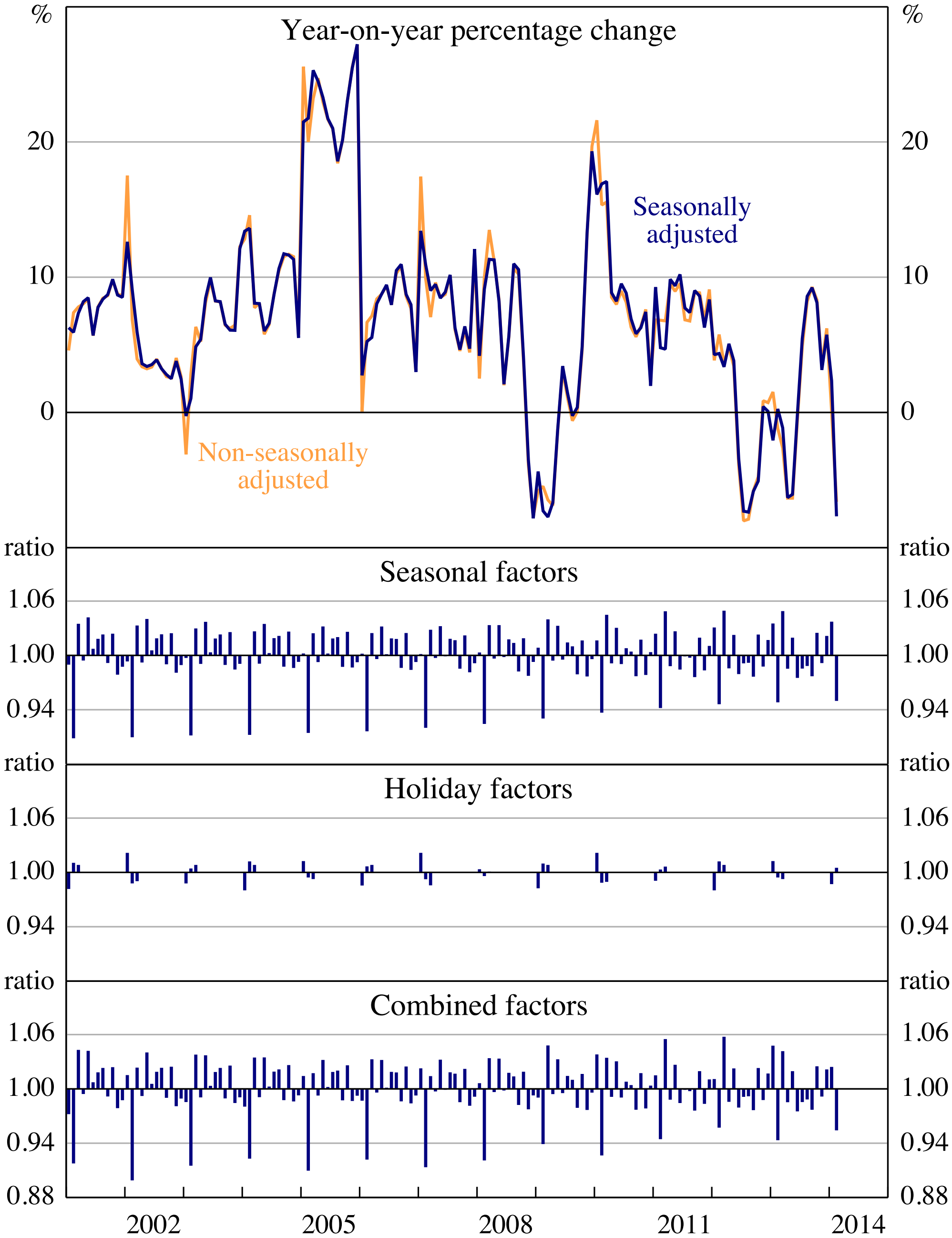
Figure C4: Credit



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure

Sources: Authors' calculations; CEIC Data

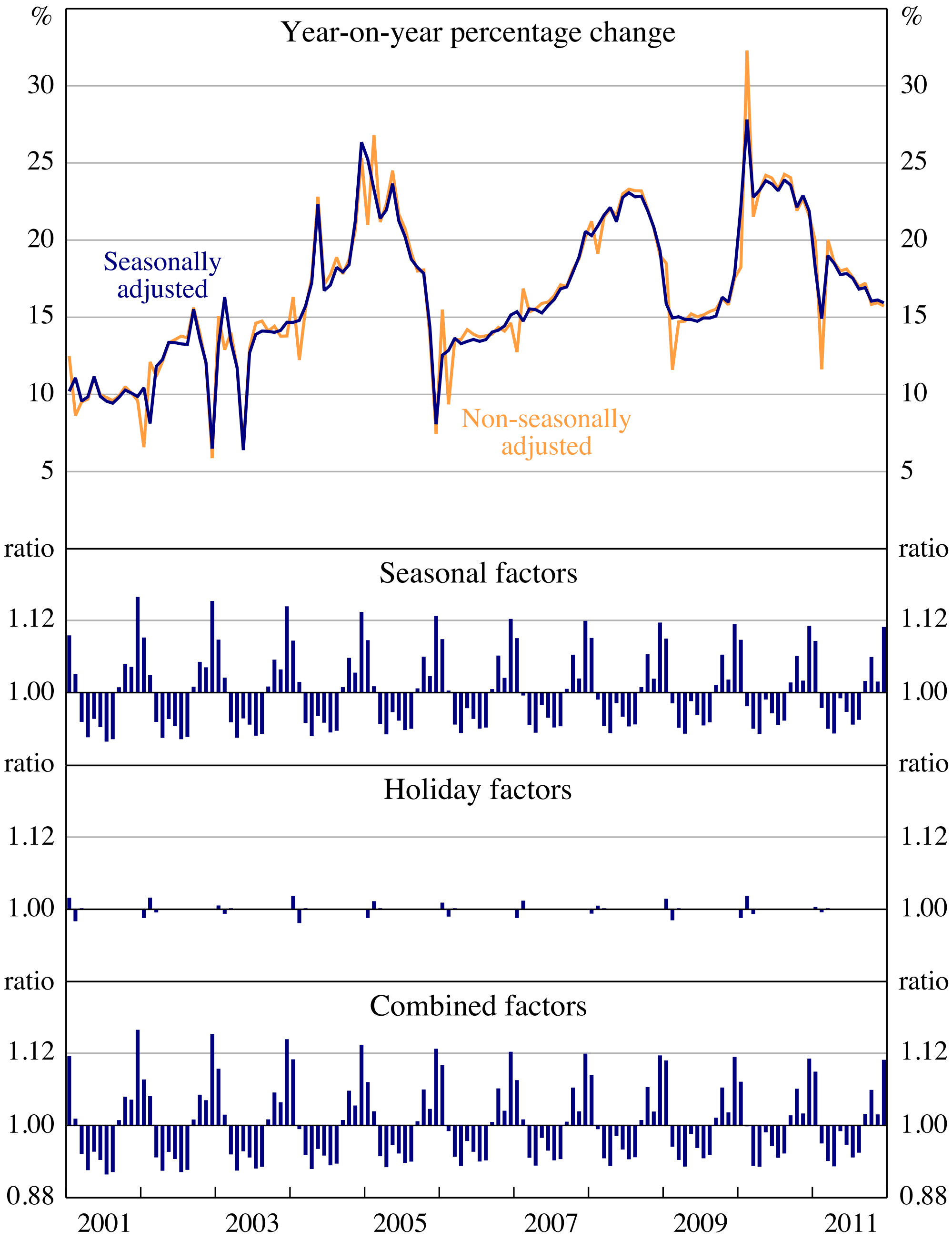
Figure C5: Rail Freight



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure

Sources: Authors' calculations; CEIC Data

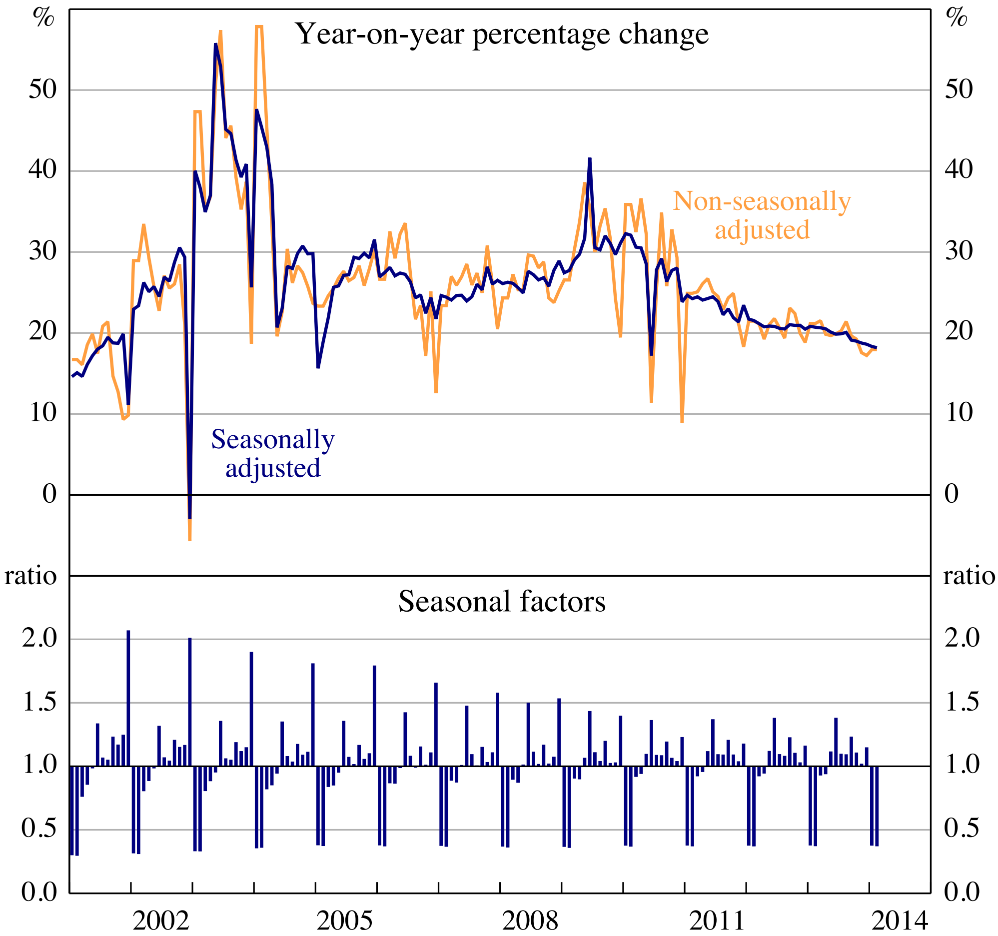
Figure C6: Retail Sales



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure

Sources: Authors' calculations; CEIC Data

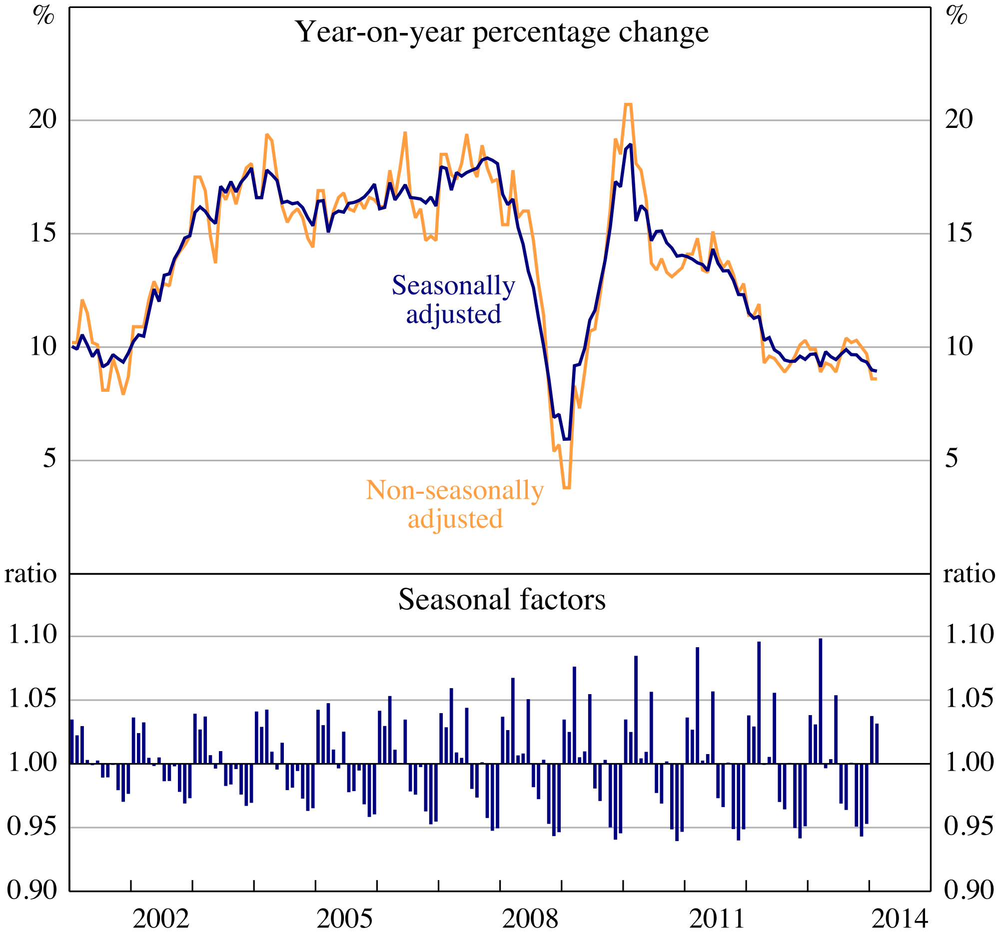
Figure C7: Fixed Asset Investment



Note: The estimates in this figure have been produced using the SEATS-ARIMA procedure

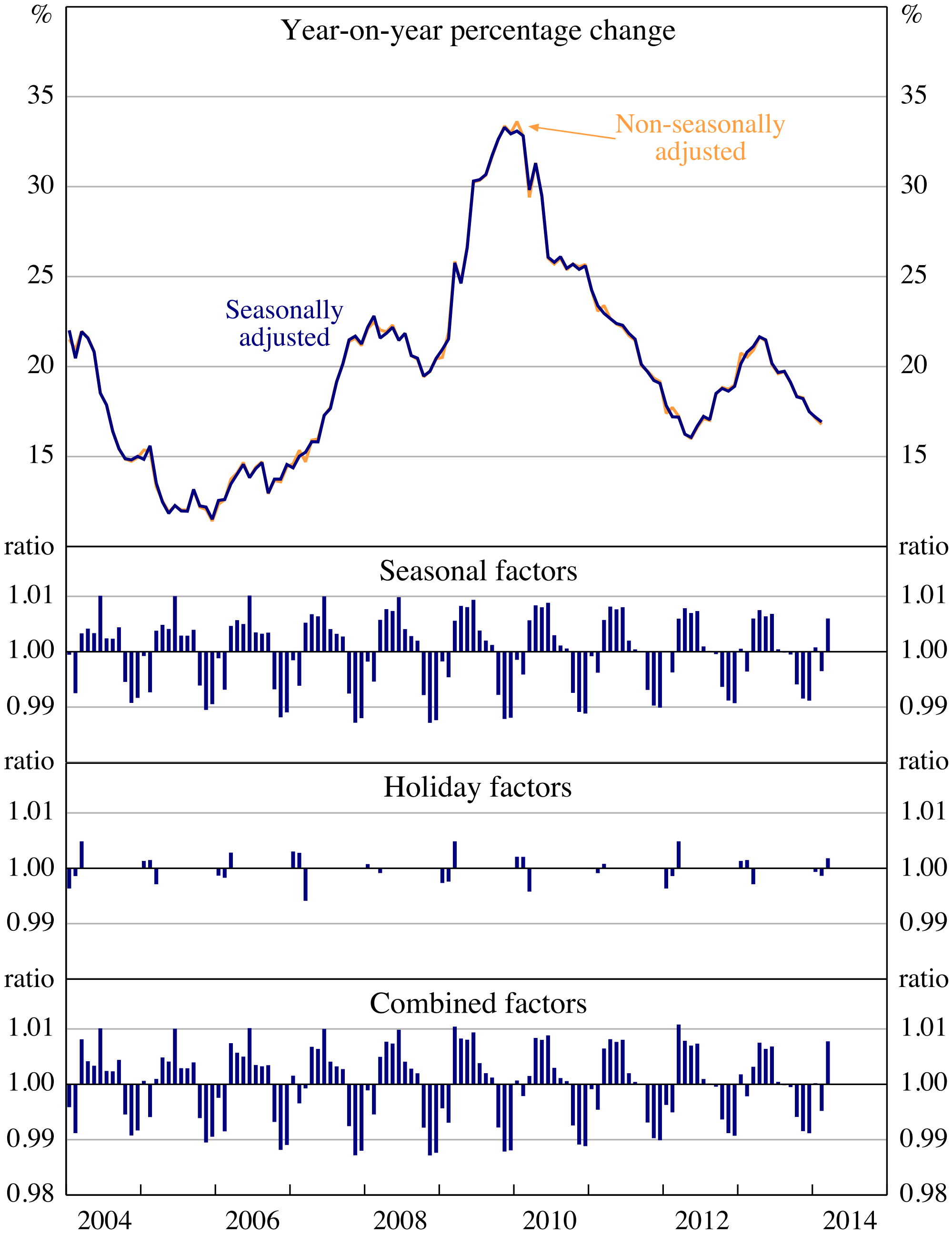
Sources: Authors' calculations; CEIC Data

Figure C8: Industrial Production



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure
Sources: Authors' calculations; CEIC Data

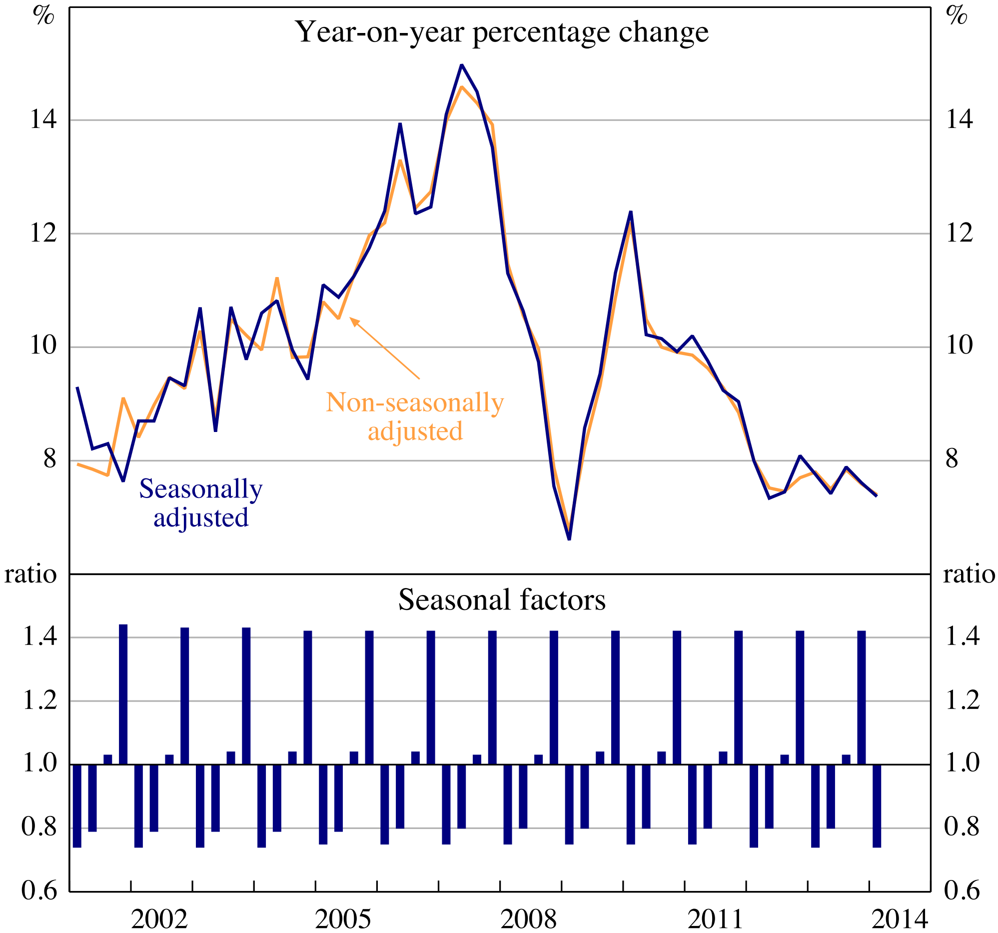
Figure C9: Total Social Financing



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure

Sources: Authors' calculations; CEIC Data

Figure C10: Real GDP



Note: The estimates in this figure have been produced using the X-12-ARIMA procedure
Sources: Authors' calculations; CEIC Data

References

Batson A (2013), 'Economic Survey', *China Economic Quarterly*, March, pp 3–5.

Bell WR and SC Hillmer (1983), 'Modeling Time Series with Calendar Variation', *Journal of the American Statistical Association*, 78(383), pp 526–534.

Bell WR and SC Hillmer (1984), 'Issues Involved with the Seasonal Adjustment of Economic Time Series', *Journal of Business & Economic Statistics*, 2(4), pp 291–320.

Burman JP (1980), 'Seasonal Adjustment by Signal Extraction', *Journal of the Royal Statistical Society: Series A (General)*, 143(3), pp 321–337.

Chang I, GC Tiao and C Chen (1988), 'Estimation of Time Series Parameters in the Presence of Outliers', *Technometrics*, 30(2), pp 193–204.

Cheung Y-W, MD Chinn and XW Qian (2012), 'Are Chinese Trade Flows Different?', NBER Working Paper No 17875.

Dagum EB (1975), 'Seasonal Factor Forecasts from ARIMA Models', *Bulletin of the International Statistical Institute: Proceedings of the 40th Session: Contributed Papers*, Vol 46 Book 3, Central Statistical Office of Poland, Warsaw, pp 203–216.

Dagum EB (1976), 'X-11, the Magic Box and Four Golden Rules of Seasonal Adjustment', Paper presented at the North American Conference on Labor Statistics, Ottawa, 25–29 July.

Delatte A-L, J Fouquau and CA Holz (2011), 'Explaining Money Demand in China during the Transition from a Centrally Planned to a Market-Based Monetary System', Bank of Finland Institute for Economies in Transition (BOFIT) Discussion Papers 27/2011.

Fernald J, I Malkin and MM Spiegel (2013), 'On the Reliability of Chinese Output Figures', *FRBSF Economic Letter* No 2013-08.

Fernald J, MM Spiegel and ET Swanson (2014), 'Monetary Policy Effectiveness in China: Evidence from a FAVAR Model', Federal Reserve Bank of San Francisco Working Paper No 2014-07.

Findley DF, BC Monsell, WR Bell, MC Otto and B-C Chen (1998), 'New Capabilities and Methods of the X-12-ARIMA Seasonal-Adjustment Program', *Journal of Business & Economic Statistics*, 16(2), pp 127–152.

Findley DF, BC Monsell, HB Shulman and MG Pugh (1990), 'Sliding-Spans Diagnostics for Seasonal and Related Adjustments', *Journal of the American Statistical Association*, 85(410), pp 345–355.

Findley DF and RJ Soukup (2000), 'Modeling and Model Selection for Moving Holidays', United States Census Bureau, X-13ARIMA-SEATS Seasonal Adjustment Program, Seasonal Adjustment Paper.

Franses PH (1996), 'Recent Advances in Modelling Seasonality', *Journal of Economic Surveys*, 10(3), pp 299–345.

Garcia-Herrero A and T Koivu (2009), 'China's Exchange Rate Policy and Asian Trade', BIS Working Paper No 282.

Ghysels E (1988), 'A Study toward a Dynamic Theory of Seasonality for Economic Time Series', *Journal of the American Statistical Association*, 83(401), pp 168–172.

Gómez V and A Maravall (1998), 'Guide for Using the Programs TRAMO and SEATS (Beta Version: December 1997)', Banco de España Documento de Trabajo No 9805.

Hererias MJ (2013), 'Seasonal Anomalies in Electricity Intensity across Chinese Regions', *Applied Energy*, 112, pp 1548–1557.

Holz CA (2013), 'The Quality of China's GDP Statistics', Stanford Center for International Development Working Paper No 487.

Hurvich CM and C-L Tsai (1989), 'Regression and Time Series Model Selection in Small Samples', *Biometrika*, 76(2), pp 297–307.

Jia Y and TM Sinclair (2013), 'Permanent and Transitory Macroeconomic Relationships between China and the Developed World', in Y-W Cheung and J de Haan (eds), *The Evolving Role of China in the Global Economy*, CESifo Seminar Series, The MIT Press, Cambridge, pp 83–106.

Ladiray D and B Quenneville (2001), *Seasonal Adjustment with the X-11 Method*, Lecture Notes in Statistics, Vol 158, Springer, New York.

Larson C (2014), 'Watching the World's Largest Human Migration as China Goes Home for the Holidays', Bloomberg Businessweek, 30 January. Available at <http://www.bloomberg.com/bw/articles/2014-01-30/watching-the-worlds-largest-human-migration-as-china-goes-home-for-the-holidays>.

Lin J-L and T-S Liu (2003), 'Modeling Lunar Calendar Holiday Effects in Taiwan', *Taiwan Economic Forecast and Policy*, 33(2), pp 1–37.

Liou S-M, L-H Lin and C-N Peng (2012), 'Using High Frequency Data to Model Moving Holiday Effects: An Empirical Investigation of Taiwanese Monetary Aggregates', *Taiwan Economic Forecast and Policy*, 43(1), pp 171–192.

Lothian J and M Morry (1978), 'A Test for the Presence of Identifiable Seasonality when Using the X-11-ARIMA Program', Statistics Canada Seasonal Adjustment and Time Series Analysis Staff Research Paper.

Lytras DP, RM Feldpausch and WR Bell (2007), 'Determining Seasonality: A Comparison of Diagnostics from X-12-ARIMA', *Proceedings of the Third International Conference on Establishment Surveys: June 18-21, 2007, Montreal, Canada*. American Statistical Association, Alexandria, pp 848–855.

Maravall A (1999), 'Unobserved Components in Economic Time Series', in MH Pesaran and M Wickens (eds), *The Handbook of Applied Econometrics: Volume 1: Macroeconomics*, Blackwell Handbooks in Economics, Blackwell Publishers Ltd, Oxford, pp 12–72.

Marquez J and J Schindler (2007), 'Exchange-Rate Effects on China's Trade', *Review of International Economics*, 15(5), pp 837–853.

Monsell BC (2009), 'Update on the Development of X-13ARIMA-SEATS', United States Census Bureau, X-13ARIMA-SEATS Seasonal Adjustment Program, Seasonal Adjustment Paper.

Nerlove M (1964), 'Spectral Analysis of Seasonal Adjustment Procedures', *Econometrica*, 32(3), pp 241–286.

Orlik T (2011), 'Q-on-Q Seasonally Adjusted Annualized GDP—It's Important!', *The Wall Street Journal* China Real Time blog, 14 April. Available at <http://blogs.wsj.com/chinarealtime/2011/04/14/q-on-q-seasonally-adjusted-annualized-gdp%e2%80%94its-important/>.

PBC (People's Bank of China Research and Statistics Department) (2006), *X-12-ARIMA: Seasonal Adjustment — Principles and Methods* (in Chinese), China Financial Publishing House, Beijing.

Perng F-N (1982), 'Seasonal Adjustment on Monetary Aggregates: Moving Holiday Effects of Chinese New Year in Seasonal Adjustment Procedure on Currency and Demand Deposits', *Central Bank of China Quarterly Bulletin*, 4(1), pp 8–55.

Pollock DSG (2002), 'A Review of TSW: The Windows Version of the TRAMO–SEATS Program', *Journal of Applied Econometrics*, 17(3), pp 291–299.

Saijo H (2013), 'Estimating DSGE Models Using Seasonally Adjusted and Unadjusted Data', *Journal of Econometrics*, 173(1), pp 22–35.

Scott S, R Tiller and D Chow (2007), 'Empirical Evaluation of X-11 and Model-Based Seasonal Adjustment Methods', Bureau of Labor Statistics, Office of Survey Methods Research, Statistical Survey Paper.

Shiskin J, AH Young, and JC Musgrave (1967), 'The X-11 Variant of the Census Method II Seasonal Adjustment Program', US Department of Commerce, Bureau of the Census, Technical Paper No 15.

Shu C and A Tsang (2005), 'Adjusting for the Chinese New Year: An Operational Approach', Hong Kong Monetary Authority Research Memorandum 22/2005.

Shuja N, MA Lazim and YB Wah (2007), 'Moving Holiday Effects Adjustment for Malaysian Economic Time Series', Unpublished manuscript, Department of Statistics Malaysia.

Sun R (2013), 'Does Monetary Policy Matter in China? A Narrative Approach', *China Economic Review*, 26, pp 56–74.

Tang S, EA Selvanathan and S Selvanathan (2012), *China's Economic Miracle: Does FDI Matter?*, Edward Elgar Publishing Limited, Cheltenham.

Woon SE (2011), ‘Seasonal Adjustment of Monthly Economic Time Series in Korea: A Comparison of X-12-ARIMA and TRAMO-SEATS’, Unpublished manuscript, Statistics Korea.

Zuo H and SY Park (2011), ‘Money Demand in China and Time-Varying Cointegration’, *China Economic Review*, 22(3), pp 330–343.

RESERVE BANK OF AUSTRALIA