SEASONAL ADJUSTMENT OF HONG KONG'S MONETARY STATISTICS

This paper examines the significance of seasonal effects on monetary statistics, and considers if seasonal adjustments need to be made to the monthly data. Test statistics indicate strong evidence of seasonality for currency held by the public, demand deposits, and HK$M1. On the other hand, the evidence suggests that seasonality is not significant for HK$M2 and HK$M3. Before deseasonalising currency held by the public and demand deposits with conventional seasonal adjustment technique, a special high frequency filtering is used to take into account increased currency holdings due to the Chinese New Year, and adjustments are made for the increase in cash demand associated with Y2K in the currency series, and increases in demand deposits due to initial public offers. Starting from November 2000, the HKMA plans to publish monthly seasonally adjusted series for currency, demand deposits, and HK$M1.

I. Purpose

Currently, no seasonally adjusted monetary aggregates are compiled in Hong Kong. In order to facilitate economic and financial analysis, this paper examines the significance of seasonal effects on the monetary statistics, and considers if seasonal adjustments need to be made to the monthly data. The paper is organised as follows: Section II provides a brief review of seasonal adjustment methods; Section III outlines the scope and method of study; Section IV identifies and removes extreme values; Section V conducts tests for the presence of seasonality; Section VI considers holiday effects; Section VII provides a seasonally adjusted aggregate HK$M1 series; Section VIII outlines the arrangements for publication of seasonally adjusted data; and Section IX presents conclusions.

II. A Review of Seasonal Adjustment

Economic trends sometimes cannot be easily inferred from direct inspection of the unadjusted values of monthly or quarterly time series. The reason is that in most economic time series differences between successive unadjusted values reflect - inter alia - seasonal effects that obscure the underlying trend. If the most recent values are compared with the corresponding values a year ago, it is possible to obtain, as an approximation, a time series free of seasonal fluctuations. However, an approach based on year-on-year comparisons has the defect that the rate of change obtained using the two values includes developments over the preceding twelve months. Thus, recent trends in the data may not be well reflected in year-on-year comparisons.

One useful method to obtain a more current view of underlying trends in the data is to apply seasonal adjustment to the time series. The purpose of seasonal adjustment is to eliminate effects that can, under normal circumstances, be expected to recur at definite times each year, thus enabling figures for consecutive months or quarters to be compared more meaningfully.

On the technical front, most seasonal adjustment techniques are basically methods of computing seasonal indices (which attempt to measure the seasonal variation in the series). Those indices are then used to deseasonalise (i.e. seasonally adjust) the series by removing the seasonal variations. Several methods are available for this purpose. Apart from regression models, most of them involve moving average filters. The difference between moving average procedures mainly lies in the way the filter is constructed. With techniques such as X-11 and its variants, the filter is empirical, in the sense that it does not depend on prior judgements of the statistical properties of the series under analysis. The general moving average procedures are explained as follows.

Seasonal adjustment techniques are based on the idea that a time series Y_t can be represented as the product of four components:

$$Y_t = L \times S \times C \times I, \tag{II.1}$$

where :

- L and C are Trend-Cycle components that represent the long-term and medium-to-long term movements of the series, including consequential turning points.
- S is the seasonal component that represents within-year fluctuations about the trend that recur in a similar way in the same month or quarter from year to year.
- I is the residual component that remains after seasonal and trend components are removed from the series (and also trading day and holidays effects, once these have been identified). It is characterised by movements of very short duration. These can be quite large if there are strikes or other unusual economic events of short duration.

To eliminate the seasonal component S, the first step is to identify the combined long-term trend and cyclical component (i.e., $L \times C$), by applying a simple moving average procedure. For example, suppose Y_t consists of monthly data, then a 12-month two-sided moving average of $\tilde{y}_t$ is computed:

$$\tilde{y}_t = \frac{1}{12}(Y_{t+6} + \ldots Y_t + Y_{t-1} + \ldots + Y_{t-5}). \tag{II.2}$$

Presumably, $\tilde{y}_t$ is relatively free of seasonal and irregular fluctuations, and is thus an estimate of $L \times C$. The second step is to divide the original data by this estimate of $L \times C$ to obtain an estimate of the combined seasonal and irregular components $S \times I$:

$$\frac{LxSxCxI}{LxC} = S \times I = \frac{y_t}{\tilde{y}_t} = z_t. \tag{II.3}$$

The next step is to eliminate the irregular component I in order to obtain the seasonal index. To do this, the values of $S \times I$ corresponding to the same month are averaged. In other words, suppose that Y_1 (and hence z_1) corresponds to January, Y_2 to February, etc., and that there are 48 months of data, the following is computed:

$$\tilde{z}_1 = \frac{1}{4}(z_1 + z_{13} + z_{25} + z_{37})$$

$$\tilde{z}_2 = \frac{1}{4}(z_2 + z_{14} + z_{26} + z_{38})$$

....

$$\tilde{z}_{12} = \frac{1}{4}(z_{12} + z_{24} + z_{36} + z_{48}). \tag{II.4}$$

The rationale here is that, when the seasonal-irregular percentages z_t are averaged for each month (each quarter if the data are quarterly), the irregular fluctuations will be largely smoothed out.

The 12 averages $\tilde{z}_1, \ldots, \tilde{z}_{12}$ will then be estimates of the seasonal factors. They should sum to close to 12, but will not do so exactly if there is any long-run trend in the data. Seasonal factors are computed by multiplying the factors in Equation 4 by a scalar that brings their sum to 12. (For example, if $\tilde{z}_1, \ldots, \tilde{z}_{12}$ add to 11.8, multiply each by 12.0/11.8 so that the revised indices add to 12.). The final seasonal factors are denoted by $\bar{z}_1, \ldots, \bar{z}_{12}$.

Finally, deseasonalisation of the original series y_t is now straightforward: just divide each value by its corresponding seasonal factor, thus removing the seasonal component while leaving the other three components. That is, the seasonally adjusted series y_t^a is obtained from $y_1^a = \frac{y_1}{\bar{z}_1}, \ldots, y_{14}^a = \frac{y_{14}}{\bar{z}_2}$, etc.

III. Scope and Methodology of Study

Three Hong Kong dollar monetary aggregates are often used in economic and monetary analysis: HK$M1, HK$M2 and HK$M3. The composition of these aggregates is as follows.

- HK$M1: Currency held by the public + customers' demand deposits with licensed banks.

- HK$M2: HK$M1 + customers' savings and time deposits with licensed banks + negotiable certificates of deposits issued by licensed banks and held by the public.

- HK$M3: HK$M2 + customers' deposits with restricted license banks and deposit-taking companies + negotiable certificates of deposits issued by such institutions and held by the public.

All aggregates are available on a monthly basis. This paper covers data from January 1985 to December 1999. Charts 1 to 5 depict the movements in the monetary aggregates and the components of HK$M1 over this period. They also show the patterns of movement through the year for recent years, to provide a visual indication of possible seasonality in the data and its stability. Three main characteristics can be observed. First, the plot of HK$M2, HK$M3 and currency showed that all of them have been steadily growing for the entire 15-year period, implying a strong trend. HK$M1 and demand deposits also increased steadily during the period under review except in 1997 and 1998. Second, one-off spikes were observed in HK$M1 and demand deposits. Third, there were apparent recurring patterns in HK$M1, currency held by the public, and demand deposits, reflecting a presence of seasonality.

The X-12 ARIMA seasonal adjustment programme, the latest seasonal adjustment programme of the US Bureau of the Census, is the general tool that we use to test and adjust for the presence of seasonality in the monetary aggregates (Box 1). As will be explained later, however, the use of the regARIMA model feature of the X-12 ARIMA programme is not effective in removing the Chinese New Year (CNY) effect on cash holdings by the public, and an alternative method was designed specifically to adjust the Hong Kong dollar currency series for the CNY effect.

IV. Identification and Adjustments for Extreme Values

It is often useful to judgementally remove one-off data irregularities before applying seasonal adjustment to a series. The different types of data irregularities that are considered in the context of seasonal adjustment are additive outliers (AO), temporary changes (TC), and level shifts (LS). An AO is thus able to catch a single point jump in the data, a TC captures a single point jump followed by a smooth return to the original path, and a LS a permanent change in the level of the series. The X-12 ARIMA programme performs the outlier detection and identification estimation in an automatic way. The methodology for outlier detection, identification, and estimation has been developed by, among others, Chang, Tiao and Chen (1988, Technometrics) and consists of the following procedures:

- A model is fitted to the series, and the residuals e_t are obtained.

- For every residual, estimators for the three types of outlier w_a, w_t, w_l are computed together with their t-values.

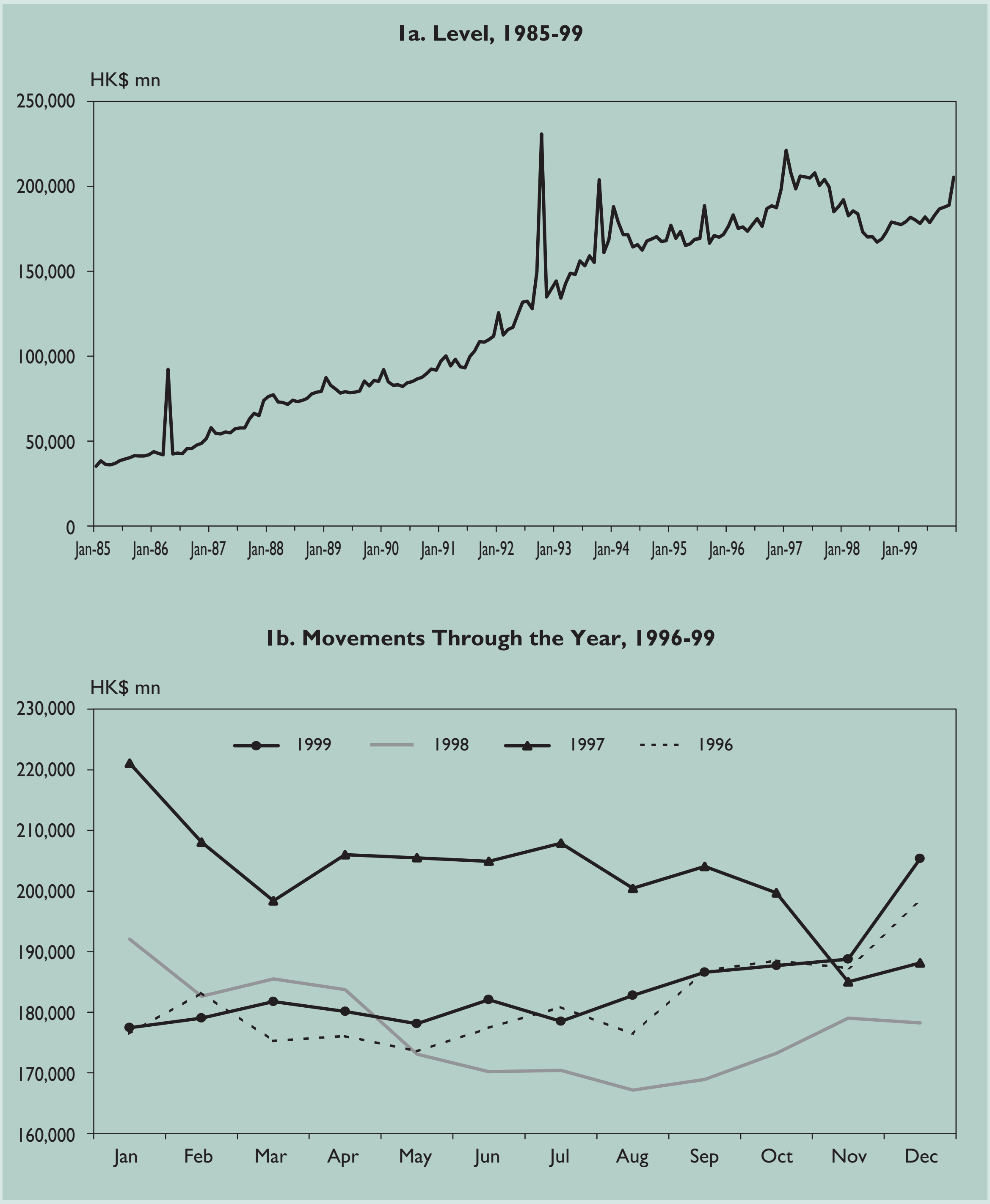
- When the t-value for a specific w exceeds a critical value, then an outlier at time t is detected.

From the plots of month-end data series for HK$M1, HK$M2, and HK$M3[1], there are several obvious non-regular sharp spikes in these series (Charts 1-3). In checking the data series of the components of the monetary aggregates, it was found that such spikes were a result of changes in demand deposits that were mostly related to new

1 Monetary aggregates are complied from a monthly "Returns of Assets and Liabilities" of all authorized institutions in Hong Kong. Banks are required to submit their positions of the last calendar day of each month to the HKMA.

Chart 1

HK$M1

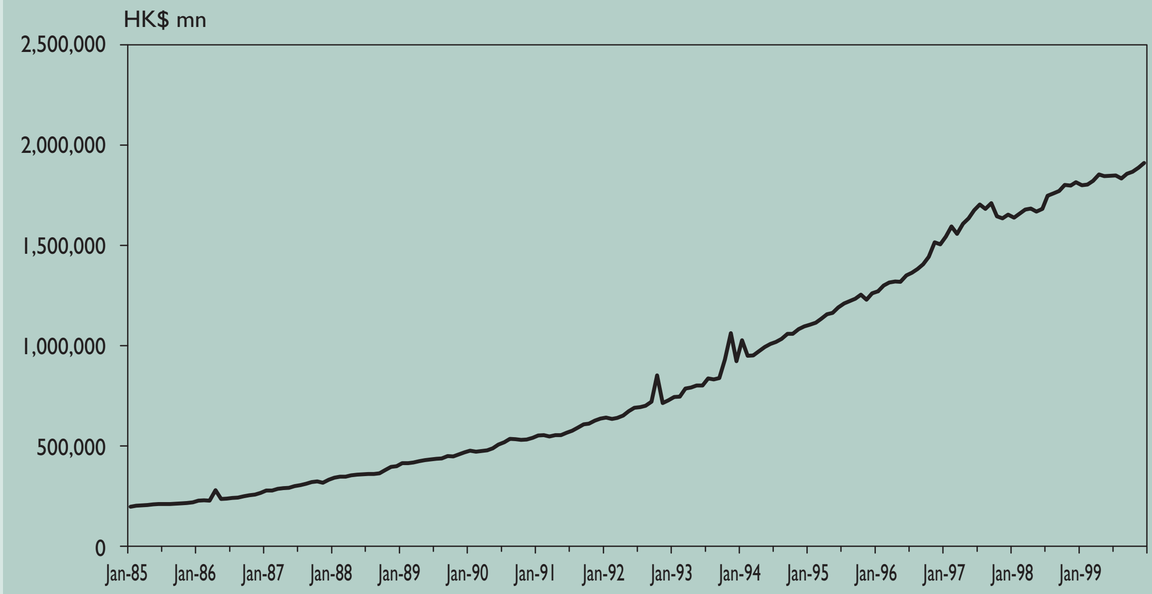


1a. Level, 1985-99
HK$ mn
250,000
200,000
150,000
100,000
50,000
0
Jan-85
Jan-86
Jan-87
Jan-88
Jan-89
Jan-90
Jan-91
Jan-92
Jan-93
Jan-94
Jan-95
Jan-96
Jan-97
Jan-98
Jan-99
1b. Movements Through the Year, 1996-99
HK$ mn
230,000
220,000
210,000
200,000
190,000
180,000
170,000
160,000
1999
1998
1997
1996
Jan
Feb
Mar
Apr
May
Jun
Jul
Aug
Sep
Oct
Nov
Dec

Chart 2

HK$M2

2a. Level, 1985-99



2b. Movements Through the Year, 1996-99

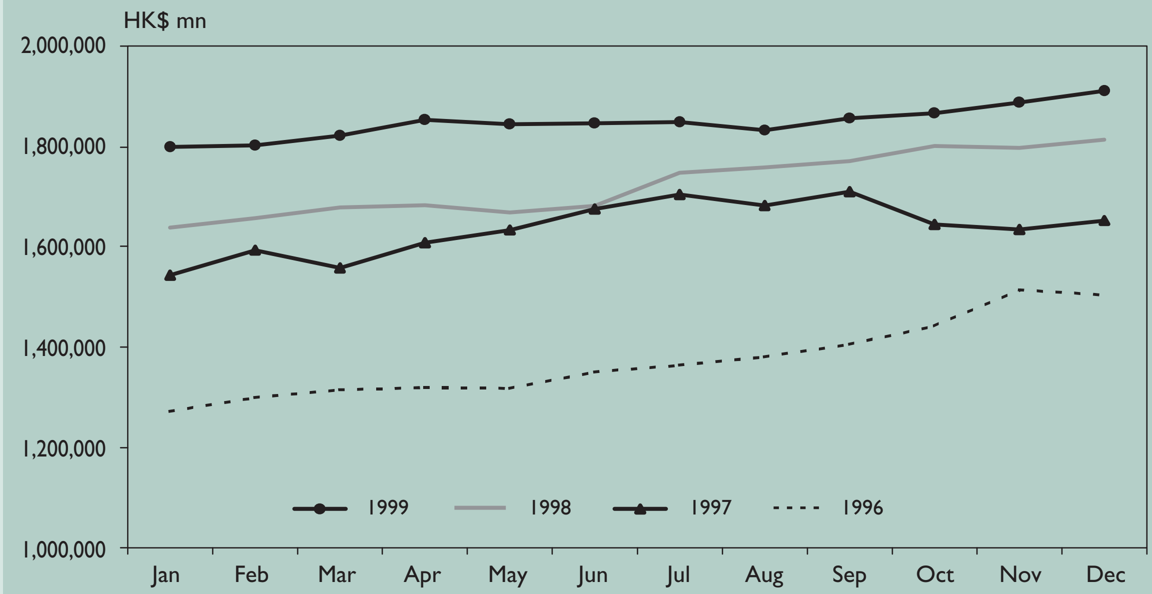
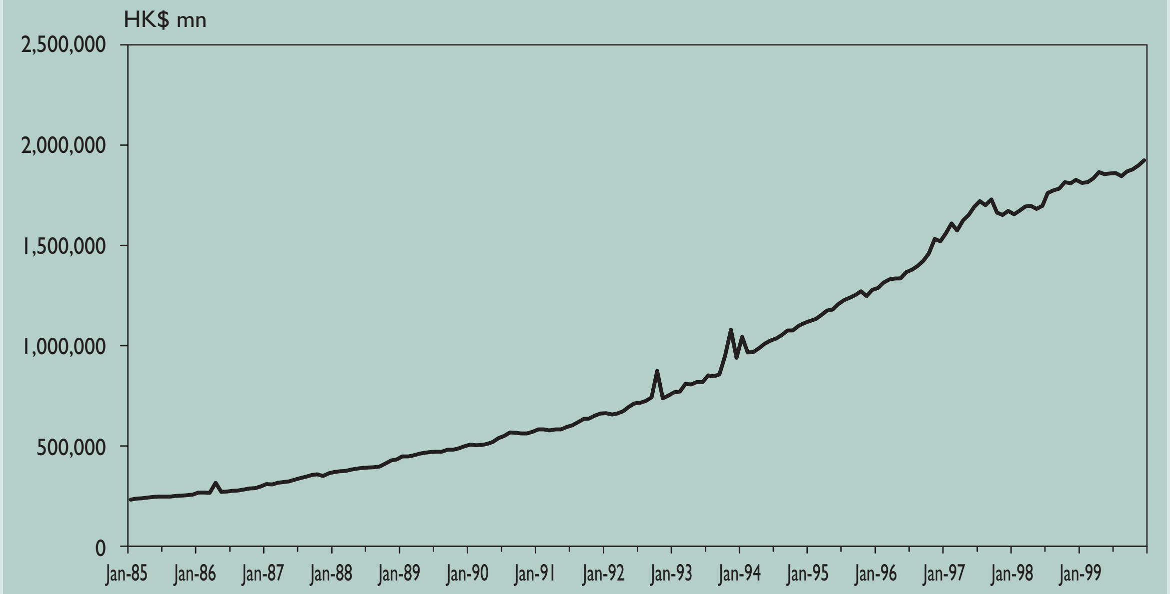


Chart 3

HK$M3

3a. Level, 1985-99



3b. Movements Through the Year, 1996-99

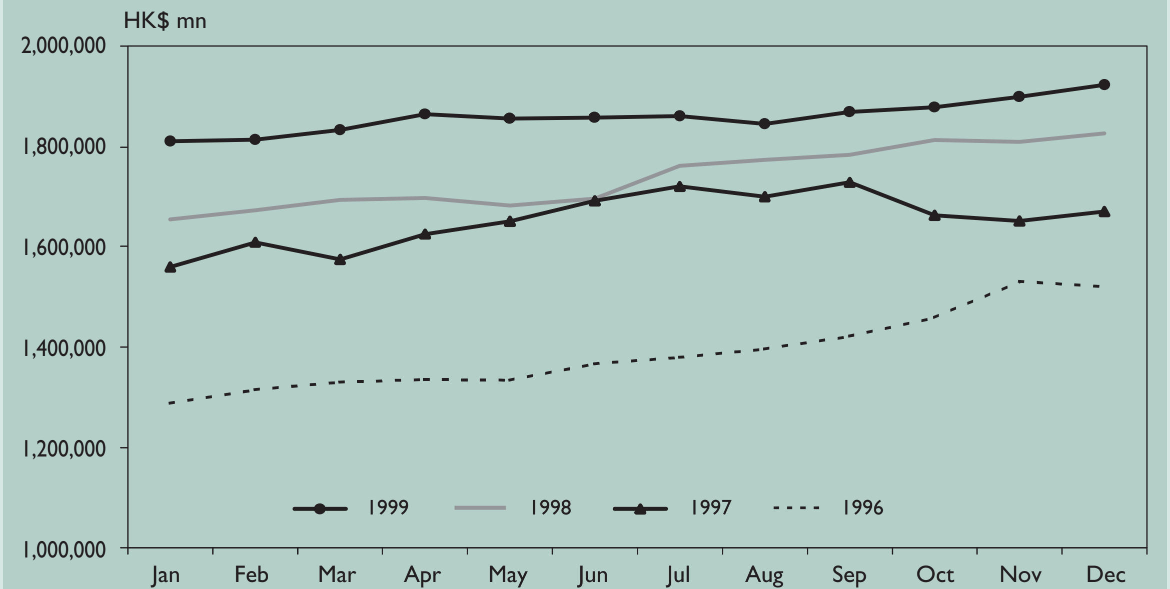
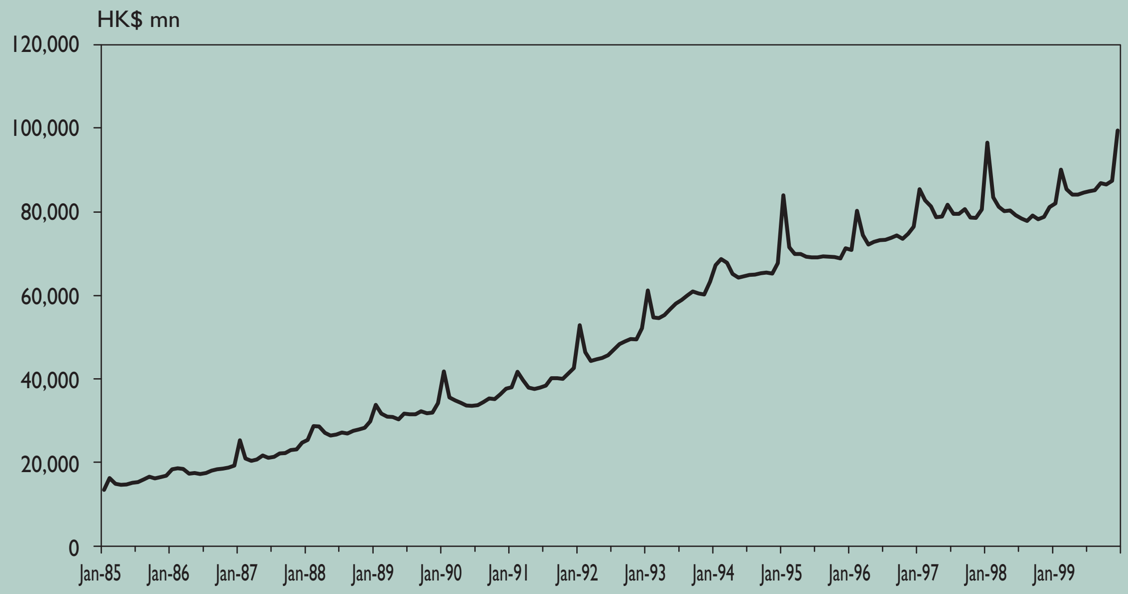


Chart 4

Currency Held by the Public

4a. Level, 1985-99



4b. Movements Through the Year, 1996-99

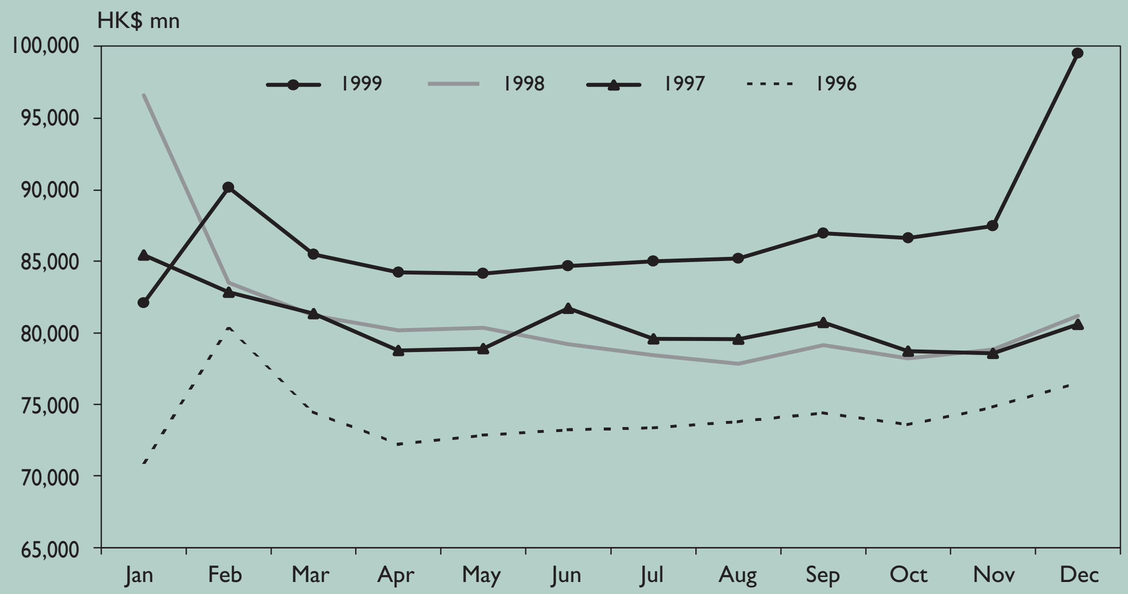
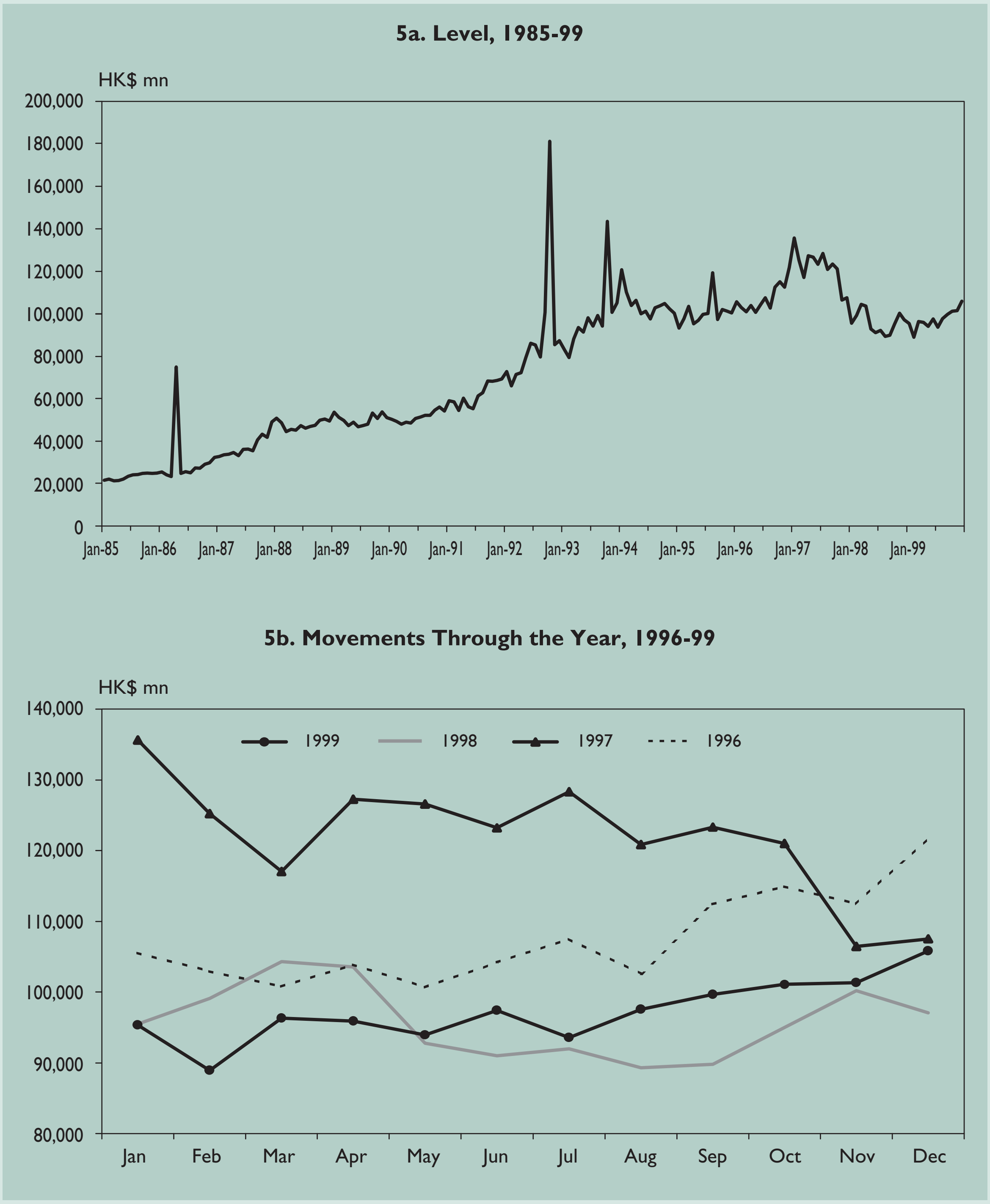


Chart 5

Demand Deposits



Box 1
X-12 ARIMA

The X-12 ARIMA programme belongs to the methodological lineage of the US Census Bureau's X-11 programme and Statistics Canada's X-11 ARIMA and X-11 ARIMA/88 programmes. It contains standard seasonal adjustment methods used by the US Bureau of Census and other statistical bureaux to adjust data for seasonal effects. The X-12 ARIMA programme consists of three parts that build upon one another.

The first part, which is not found in the old X-11 programme, generates mathematical models of the unadjusted series using the regARIMA technique; this technique combines the tools of regression analysis with the ARIMA (auto-regressive integrated moving average) approach. Mathematical criteria are used to characterise certain properties of the time series; this information, can, in turn, be employed in the second part for specifying the seasonal estimation procedure. RegARIMA models are regression models with ARIMA (autoregressive integrated moving average) errors. More precisely, they are models in which the mean function of a time series (or its logs) is described by a linear combination of regressors, and the covariance structure of the series is that of an ARIMA process. If no regressors are used, indicating that the mean is assumed to be zero, the regARIMA model reduces to an ARIMA model. There are built-in regressors for directly estimating various trading day effects and holiday effects (such as Easter holidays and Thanksgiving). There are also regressors for modelling certain kind of disruptions in the series, or sudden changes in level, whose influences need to be temporarily removed from the data before the X-11 methodology can adequately estimate seasonal adjustments. To address data problems not provided for, there is the capability of incorporating user-defined regression variables into the model fitted. The regARIMA modelling module of X-12 ARIMA was adapted from regARIMA programme developed by the Time Series Staff of Bureau of Census' Statistical Research Division.

The specification of a regARIMA model requires determining both the variables to be included in the model and also the type of ARIMA model for the regression errors. Specification of the regression variables depends on user knowledge about the series being modelled. Once a regARIMA model has been specified, X-12 ARIMA will estimate its parameters by maximum likelihood using an iterative generalised least squares (IGLS) algorithm. Annex 1 shows a general regARIMA model.

The second part of the X-12 programme basically consists of the old X-11 programme[2], and is used to perform the actual seasonal adjustment. If calculations have already been carried out in the regARIMA part, the estimation of the seasonally adjusted series proceeds from the results of the first stage; if not, the unprocessed unadjusted values enter the second stage directly as input. The X-12 ARIMA seasonal adjustment programme decomposes the original time series (O) into three basic components - seasonal, trend-cycle, and irregular components.

Depending mainly on the nature of the seasonal movements of a given series, several different models, namely multiplicative, additive, pseudo-additive, and log-additive models are used to describe the way in which the components C, S, and I combine to form the original series O. The multiplicative mode is chosen to perform seasonal adjustment to the money aggregates. This is because, like most economic time series, the magnitude of the seasonal fluctuations appears to increase and decrease proportionally with the level of the series. A series with this type of seasonality is said to have multiplicative seasonality. The programme uses a ratio-to-moving average method to estimate the multiplicative components.

The third part of the programme is equipped with several new diagnostics to test the quality of seasonal and calendar effect adjustments.

2 The seasonal adjustment module uses the X-11 seasonal adjustment method detailed in Shiskin, Young and Musgrave (1967) and Dagum (1988).

share listings. If the last business day of the reference month falls into the period between the closing date of application for a large initial public offering (IPO) and the refund date, the subscription money involved in the stock issuance would affect that month's monetary data. In addition, the cash holdings in December 1999 reflect a one-off increase in cash demand associated with the transition into Year 2000.

As these one-off spikes could be regarded as outliers with respect to the underlying trend in the data, the automatic outlier treatment of the X-12 ARIMA programme was used to identify and remove the spikes in demand deposits and the other monetary aggregates. Table 1 shows the outliers detected for demand deposits, HK$M1, HK$M2, and HK$M3. All the outliers were related to IPO activities, as listed in Annex 2.

Table 1
Outlier Adjustments by the X-12 ARIMA Programme

Demand Deposits	HK$M1	HK$M2	HK$M3
Apr 86	Apr 86	Apr 86	Apr 86
Sep 92	Sep 92	Oct 92	Oct 92
Oct 92	Oct 92	Oct 93	Oct 93
Oct 93	Oct 93	Nov 93	Nov 93
Aug 95	Aug 95	Jan 94	Jan 94

V. Tests for the Presence of Seasonality

Money Aggregates

After the adjustment for one-off spikes, statistical tests were performed to check whether

Table 2
Test for Seasonality: Monetary Aggregates

	Statistic	Probability Level	H0: No signs of seasonality 0.1% level[2]	1% level[3]	5% level	Remarks
HK$M1						
F-test	17.72	0.00%	Significant	Significant	Significant	Seasonality present
Nonparametric test[1]	87.56	0.00%	—	Significant	Significant	Seasonality present
HK$M2						
F-test	1.97	3.41%	Insignificant	Insignificant	Significant	Inconclusive signs of seasonality
Nonparametric test[1]	18.88	6.33%	—	Insignificant	Insignificant	Inconclusive signs of seasonality
HK$M3						
F-test	2.19	1.71%	Insignificant	Insignificant	Significant	Inconclusive signs of seasonality
Nonparametric test[1]	24.60	1.04%	—	Insignificant	Significant	Inconclusive signs of seasonality

1 *Kruskal-Wallis Chi Square test.*
2 *The default decision level for F-tests used by the X-12 programme.*
3 *The decision level for nonparametric tests used by the X-12 programme.*

seasonal effects are significant. An informal and direct way to detect whether seasonal patterns exist in time series data is by visual inspection of the raw data. With reference to Charts 1 to 3 on unadjusted HK$M1, HK$M2, and HK$M3, the appearance of spikes at roughly regular intervals over time in the HK$M1 series suggests the existence of seasonality. On the other hand, there are no obvious signs of seasonality in HK$M2 and HK$M3.

Next, two statistical tests - "F-tests" and the non-parametric "Kruskal-Wallis Chi-Square Test" provided by the X-12 ARIMA programme - were used to formally test for the presence of stable seasonality. Stable seasonality refers to the situation in which the seasonal effects occur in the same period each year throughout the time span under study. A high value of the F-statistic will lead to rejection of the null hypothesis that no significant seasonality is present in the time series. Test statistics for the F-tests and non-parametric tests for seasonal effects are presented in Table 2, indicating strong evidence of seasonal effects for HK$M1. The test statistics are not significant, however, for HK$M2 and HK$M3 at the 0.1% level (which is the default decision level for the F-test in the X-12 programme[3]). There is mixed evidence for HK$M2 and HK$M3 at the 5% level, with HK$M3 showing seasonality but HK$M2 not. The inconsistent results are somewhat puzzling, given the small difference between the HK$M2 and HK$M3 series[4].

Components of HK$M1

Further tests were conducted on the two components of HK$M1: currency held by the public, and demand deposits. Charts 4 and 5 on currency held by the public and demand deposits respectively provide obvious visual evidence of seasonal patterns in both series. Test statistics - with demand deposits adjusted for one-off spikes - formally indicate significant seasonality in both components of HK$M1 (Table 3).

VI. Holiday Effect Adjustments

A further look at the graphs of the irregular components derived from the X-12 ARIMA programme suggests that the irregular patterns in currency held by the public occur mostly in January

Table 3
Test for Seasonality: Components of HK$M1

	Statistic	H0: No signs of seasonality Probability Level	**0.1% level**	**1% level**	Remarks
Currency held by the public[1]					
F-test	25.91	0.00%	Significant	Significant	Seasonality present
Nonparametric test	129.26	0.00%	—	Significant	Seasonality present
Demand deposits[2]					
F-test	4.46	0.00%	Significant	Significant	Seasonality present
Nonparametric test	47.57	0.00%	—	Significant	Seasonality present

1 Without prior adjustment for the Chinese New Year holiday effect.
2 With prior adjustment for new share listings.

3 In reply to our enquiry on the default critical level, a Bureau of Census specialist in the US explained that the designer intentionally chose a low critical level because the normality assumption may not hold for the F-test.

4 M3 refers to the sum of M2 plus customers deposits with restricted license banks (RLBs) and deposit-taking companies (DTCs), and negotiable certificates of deposits (CDs) issued by these institutions held by the public. Such deposits and negotiable CDs represent only around 0.7% of total M3.

or February of each year (Annex 3). The pattern reflects the effect of the Chinese New Year (CNY), as the public tends to hold a greater amount of cash ahead of and around the CNY, due to traditional gift giving, and a higher number of retail transactions. The date of CNY changes every year in terms of the western calendar: it falls in January in some years and in February in others. This is referred as a "moving holiday effect", which cannot be removed by standard seasonal adjustment methods[5]. The following describes three alternative methods that were experimented with to remove such holiday effects before applying seasonal adjustment to the currency series.

First was the use of a reciprocal pair of seasonal factors to remove the CNY effect from the series for currency held by the public. This method was used in the past to remove CNY effects from the data series Certificates of Indebtedness in an article "Seasonality in the Exchange Fund" published in the HKMA *Quarterly Bulletin* in November 1996 (Annex 4). A similar method is currently being used by the Hong Kong Census and Statistics Department to pre-filter the CNY effect from the retail sales data.

For our purpose, the reciprocal factor method works as follows. As mentioned in section II, a series can be represented by four components, $Y_t = L \times S \times C \times I$, when considering seasonal effects. When moving holiday effects are present in the unadjusted data, they will primarily show up in the estimate of the irregular component (I). We thus firstly estimated irregular components for the series currency held by the public. To test for the significance of the CNY effect, the irregular components for January (I_{Jan}) were then regressed against the absolute number of days between end-January and the date of Chinese New Year (N_t). Specifically,

$$I_{Jan} = \alpha + \beta N_t + \mu.$$

By forcing the holiday factors for both January and February to 200[6], the holiday factor for February (I^a_{Feb}) was derived as (200 - I^a_{Jan}). The rationale of the summing two factors to 200 is that, if all irregular effects are evenly distributed, all the monthly factors are the same. In other words, the reciprocal factor methodology assumes that a rise in January will be followed by a reciprocal decline in February. For example, a 3% increase in cash holdings in January will be balanced out by roughly a 6% decrease in February, followed by a 3% rise in March. Thus, if the January value equals to 103, the reciprocal factor for February would be 97. Holiday-adjusted values for January and February (y^a_{Jan} and y^a_{Feb}) were estimated as follows:

$$y^a_{Jan} = (Y_{Jan} / I^a_{Jan})$$
$$y^a_{Feb} = (Y_{Feb} / (200 - I^a_{Jan})).$$

The holiday-adjusted currency series was then seasonally adjusted using conventional X-11 procedures. A comparison between the unadjusted and seasonally adjusted currency series suggests that the use of reciprocal factors for pre-holiday adjustment improves the smoothness of the adjusted series. However, as shown in Charts 6 and 7, the improvement was not sufficient to remove the CNY effect, and actually led to some distortions to the series. The problem with the reciprocal factor adjustment can be illustrated more clearly with the help of high-frequency daily data on Certificates of Indebtedness (CI)[7]. The "X-marks" in Chart 8 indicate the amount of CIs outstanding at end-January and end-February, and the "arrows" are the adjustment directions on cash holdings using the reciprocal factor methodology (a "down arrow" represents a reduction of cash holdings, while a "up arrow" represents an increase). For example, CNY started on 7 February 1997, so the increase in cash holdings occurred in January and peaked at 7 February. Based on the reciprocal factor methodology, some estimated CNY-related cash holdings were removed from the end-January

5 The effects of public holidays, if these fall on the same days every year, will be part of the seasonal. Thus, no specific adjustment is needed to capture the effects of fixed public holidays.

6 The trend-cycle and seasonal components of an unadjusted series are estimated first, and these are removed to obtain the irregular factors. The irregular factors are then multiplied by 100. Since it is desirable that the 12 monthly factors total 1200, in order that they average 100%, each of them is multiplied by an adjustment scalar. This adjustment forces a total of 1200 by lowering each of the unadjusted factors by the same percentage.

7 In Hong Kong, note issuing banks are required to submit US dollar in exchange for CIs from the Exchange Fund as cover for the banknotes they issued. The non-bank public sector holds some 90% of the notes issued.

data, and these amount were put back in February data. But, this reciprocal increase in cash holdings aggravated the volatility of the end-February data.

Chart 8 illustrates the point that "netting out" the effects on those months related to CNY (i.e. January and February) did not effectively remove the CNY impact. First, the amount of currency held by the public associated with CNY may be distributed differently from year-to-year, depending on the date of CNY. The assumption of restricting CNY effect to the first two months of the year only may not be valid. For the same reason, the assumption of "opposite direction adjustment" may not be appropriate. For example, if the CNY takes place around end-January, the currency series at end-January would be boosted. However, by the end of February, the holiday effect should disappear and cash holdings should return to their normal level. In this case, the proper adjustment is to reduce the end-January figure only. The reciprocal factor method reduces the end-January figure, but also add it back to the end-February figure, effectively shifting the holiday effect from January to February.

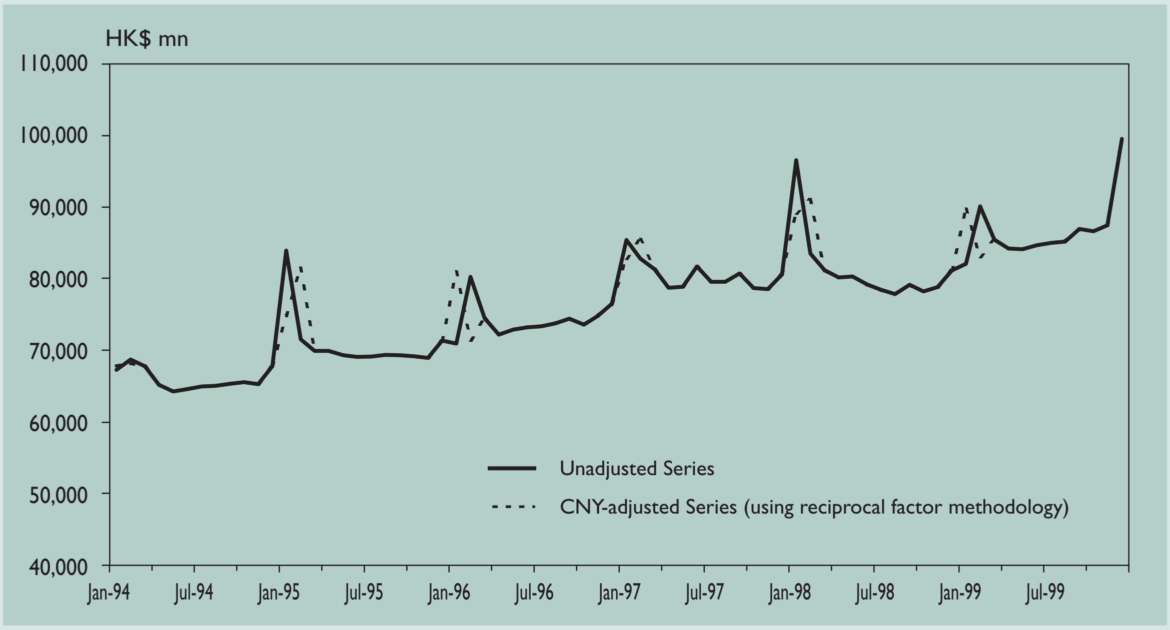
The second method used was a regARIMA model. This method is mainly used to remove special holidays such as Easter holidays and/or user-defined effects in the X-12 ARIMA programme, prior to seasonal adjustment of a flow time series. (So far the methodology has only been applied to western holidays, and the US Bureau of the Census and the Academia Sinica of Taiwan are jointly studying the effects of Chinese holidays in modelling Taiwanese data). As the pattern of Chinese New Year holiday is analogous to that of Easter, a regARIMA model was constructed to adjust for CNY holidays (Box 2). The test statistics suggested that the method only partially adjusted the CNY influences. The method did not significantly improve much of the smoothness of the series, however.

This is probably due to the fact that this regARIMA model is not likely to be appropriate for a "stock" variable like a monetary aggregate, as opposed to a "flow" variable such as retail sales, for instance. The existing method in the X-12 ARIMA programme is not designed to deal with monthly stock variables. Under the present method (Box 2), a set of holiday regressors are generated to capture the CNY effect, which is to be removed from the unadjusted currency series before it is seasonally adjusted. The estimation of the values for the CNY regressors relied on the assumption that the dependent variable (currency held by the public) is a flow series, so that the regressors capture all the effect in those months affected by the CNY holiday. Given that the CNY holiday occurred either in January or February, the date of CNY during the year implies some instability on seasonal patterns related to the months of January and February. As such, if CNY takes place around end-January and there is no CNY impact on the end-February value, it will still be adjusted. In this case, the February figure is therefore adjusted unnecessarily though the holiday effect should disappear, and cash holdings should return to their normal level.

In addition, there is a problem with the size of the adjustment. Assume that CNY occurs on 14 February, and cash holdings start to rise 25 days before CNY. In this case, cash holdings increase gradually from 21 January, and thus cash holdings on 31 January will be greater than that on 21 January. Call the holiday day effect on 21 January the 1st day effect, that on 22 January as the 2nd day effect, and so on. When there should be an adjustment for the end-January data, the adjustment should be equivalent to the holiday effect on the 11th day (i.e. 31 January). However, the regARIMA method, which assumes the currency series represents a flow, captures all the CNY effect in January. Thus it removes all the holiday effect from the 1st day to the 11th day from the end-January figure, resulting in inappropriate adjustments.

Chart 6

Currency Held by the Public



Box 2
A regARIMA Model for Chinese New Year Holiday Adjustment

The construction of a regARIMA model to adjust for the CNY holiday impact involves two steps - a selection of CNY regressors and an identification of the best-fit ARIMA model. The creation of CNY regressors uses the same procedures as the X-12 ARIMA procedure to create regressors for the Easter holidays, Labour Day, and Thanksgiving. The basic model used by the X-12 ARIMA programme for Easter holiday effects assumes that the level of activity changes on the w^{th} day before the holiday for a specified w, and remains at the new level until the day before the holiday. The Thanksgiving model assumes that the level of activity changes on the day that is a specified number of days before or after Thanksgiving, and remains at the new level until 24 December.

Regarding Easter holiday, the effect may concern either March or April, according to the year. The date of Easter during the year thus implies some instability on the seasonal patterns related to the months of March and April. For example, the increase in the purchases related to Easter starts a period of n-days before (say n=10) and ends the Saturdays before Easter. A dummy variable, say H(n, t) is created to deal with this effect. The program assumes H(n, t) = 0 for every month t except those months affected by Easter. To model the special effect on March and April, the number of days in March and in April, which belong to the interval of n-days before Easter are counted. For example, in 1999, the Easter Sunday was on 4 April: for n=10, there were seven days in March and three days in April. The regression variable H(n, t) takes the value 0.7 in March and 0.3 in April 1999.

Charts 9 and 10 on daily Certificates of Indebtedness (CIs) show that the public has a recognisable pattern of cash holding prior to and after CNY holidays. The movement of the CI series suggests that public holding of cash increases gradually around 25 days ahead of the beginning of the CNY holiday, and decreases at a similar pace after the holiday. Three regressors have been formulated to capture the effects before and after CNY, as well as the intermediate impact around CNY. A regARIMA model was then formulated to pre-adjust the CNY effect on the series of currency held by the public, before applying seasonal adjustment to the series.

Chart 7

Currency Held by the Public

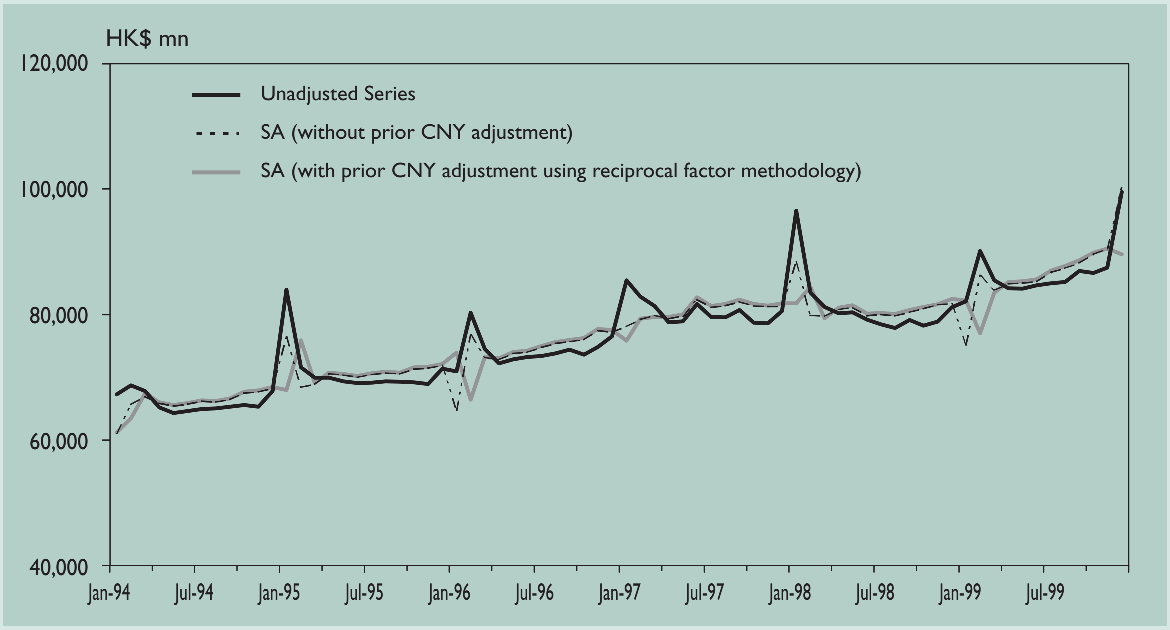


Chart 8

Adjustment Direction of the Reciprocal Factor Methodology

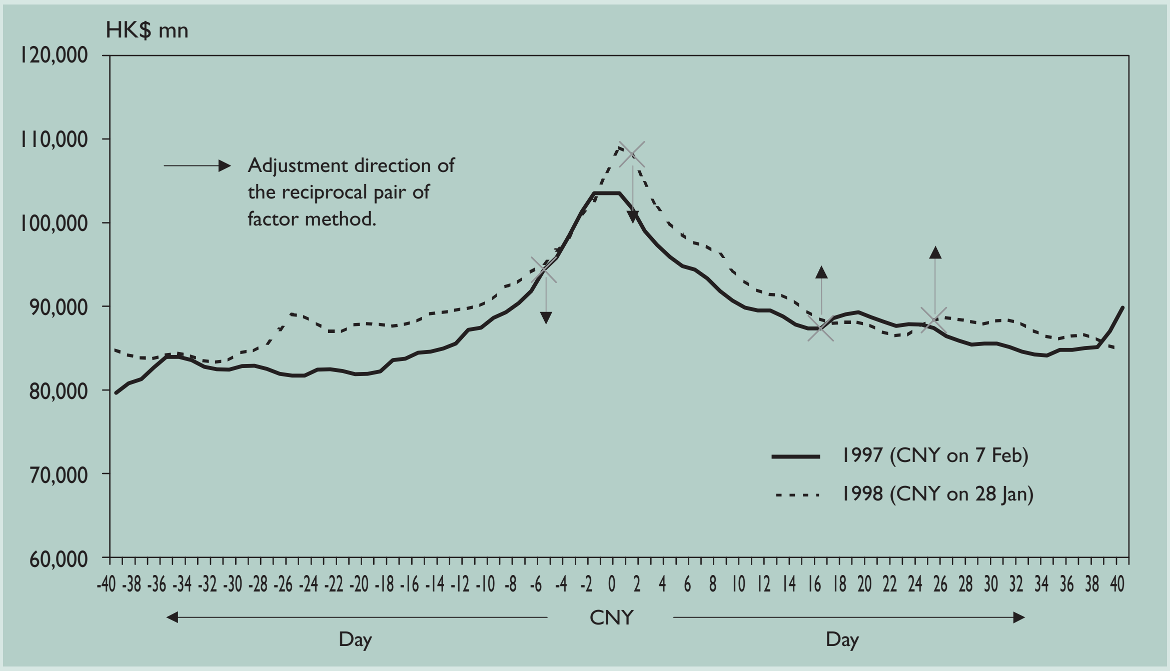
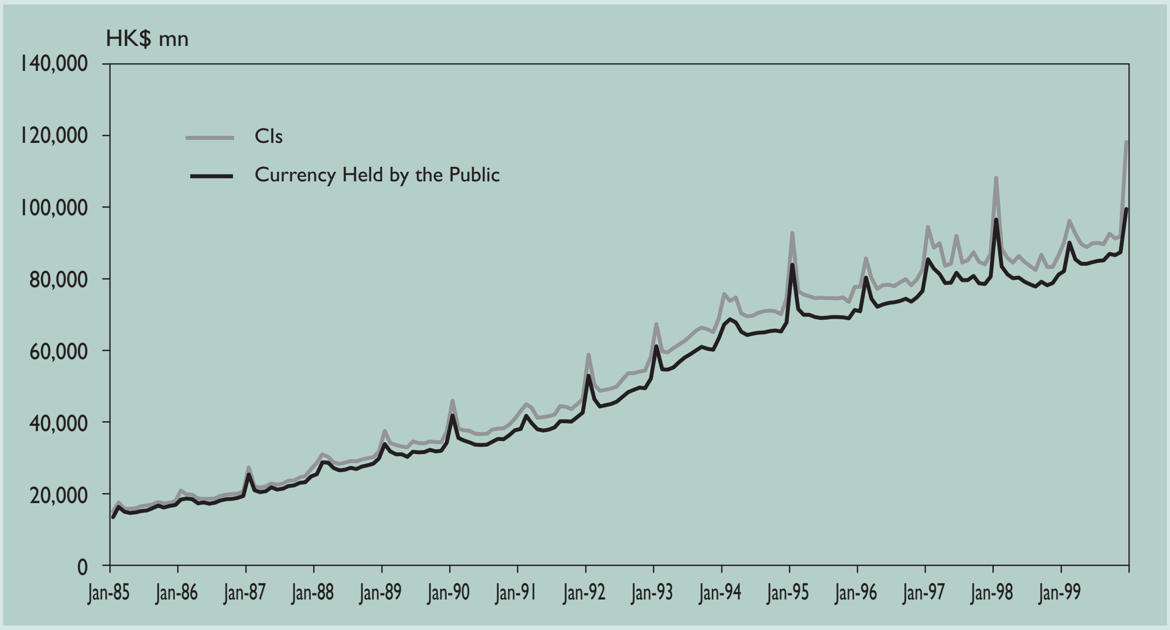


Chart 9

Certificates of Indebtedness (CIs) and Currency Held by the Public



Given a lack of success with the previous two methods, a third method was explored using high-frequency daily data to pre-filter the series to remove the CNY impact. Adjustments for the CNY effect were directly made on daily data for CIs[8], and the adjusted CI series was used to estimate CNY-adjusted monthly currency series.

Specifically, in Hong Kong, banks are required to submit US dollar in exchange for CIs from the Exchange Fund as cover for the banknotes they issue. The non-bank public typically holds some 90% of the notes issued (Chart 9). The plot on daily CIs shows that the non-bank public has a recognisable pattern of cash holdings prior to and after CNY holidays. Within the period under review here, the earliest date on which CNY occurred was January 23, and the latest date was February 20. Cash holdings gradually increase around 25 days prior to CNY, before peaking at the beginning of the CNY holiday, and decline at about the same pace after the CNY holiday. To remove the CNY effect, adjustments were made to the CI series from January to March to reflect this pattern. The estimated CNY effect on the CIs at month end was then used as a proxy for the effect on currency holdings. Details of the adjustment procedures are described as follows.

First, a daily ratio (r_{dm}) is constructed by dividing daily CIs in each year by the yearly average of CIs in that year $\overline{CI}_t$:

$$r_{dm} = CI_{dm} / \overline{CI}_t \ , \qquad \text{(VI.1)}$$

where d indicates the days of a month (1,2 ..., 31), m represents the months (January, February, ..., December), and $\overline{CI}_t$ is the average level of CIs in year t. Taking ratios is a quick way to check whether the pattern of CNY influences occurs each year. If the series is stationary, then the data should exhibit similar behaviour each year. Consistent with the above discussion, a symmetric pattern of movement before and after the CNY holidays was observed in each year (Chart 10).

Second, a series (R_d) was constructed to get an average ratio of each date that is not influenced by CNY holidays from 1 April to 31 December. To do this, the ratios corresponding to the date in the months April to December were averaged. The rationale is that, when r_{dm} of the same date in

8 Monetary aggregates are complied from the "Return on Assets and Liabilities" on a monthly basis. No daily data is available.

each month are averaged, the fluctuations will be largely smoothed out.

$$R_d = Average\ (\Sigma r_{d\,m}) \qquad (VI.2)$$

$$R_1 = 1/9\ (r_{1\,Apr} + r_{1\,May} + r_{1\,Jun} + r_{1\,Jul} + r_{1\,Aug} + r_{1\,Sep} + r_{1\,Oct} + r_{1\,Nov} + r_{1\,Dec})$$

$$R_2 = 1/9\ (r_{2\,Apr} + r_{2\,May} + r_{2\,Jun} + r_{2\,Jul} + r_{2\,Aug} + r_{2\,Sep} + r_{2\,Oct} + r_{2\,Nov} + r_{2\,Dec})$$

……………………………………………………………………………

$$R_{30} = 1/9\ (r_{30\,Apr} + r_{30\,May} + r_{30\,Jun} + r_{30\,Jul} + r_{30\,Aug} + r_{30\,Sep} + r_{30\,Oct} + r_{30\,Nov} + r_{30\,Dec})$$

$$R_{31} = 1/5\ (r_{31\,May} + r_{31\,Jul} + r_{31\,Aug} + r_{31\,Oct} + r_{31\,Dec}).$$

Next, the R_d ($d = 1,2, ..., 31$) were used as a proxy for r_{dm} from 1 January to 31 March ($R_d = r_{dm}$). The CI series for January to March (CI^a_{dm}) are derived as:

$$R_d = CI^a_{dm} / \overline{CI}_t$$
$$CI^a_{dm} = R_d \times \overline{CI}_t\ , \qquad (VI.3)$$

where CI^a_{dm} is the CNY-adjusted level of CIs in January to March.

The CNY-adjusted currency held by the public can be estimated from the CI series, as currency held by the public accounts for around 90% of the outstanding amount of CIs. This implies that the CNY-adjusted cash holdings in January to March equal to 90% of CI^a_{dm}.

$$C^a = 0.9 \times CI^a_{dm}, \qquad (VI.4)$$

where C^a is the adjusted currency held by the public in January to March.

Charts 10 and 11 depict the ratio of CIs to yearly average CIs and the CNY-adjusted ratio of CIs. Table 4 summarises the smoothness of the currency held by the public using different methods of pre-CNY adjustment. The degree of smoothness is measured by the absolute average month-on-month percentage change (S1) of the adjusted series and the standard deviation of the month-on-month percentage change (S2) of the adjusted series. In general, the method that gives rise to smaller values of S1 and S2 is preferred. The method that removes CNY effects using daily CI data to adjust the currency data has easily the lowest S1 and S2 (Chart 12). Tests for the presence of seasonality and seasonal adjustment were then performed on the CNY-adjusted series of currency held by the public to get a seasonally

Table 4
Smoothness Comparison: Seasonally Adjusted Currency Series

	CNY Adjustment Method	S1	S2
Unadjusted		3.60	5.19
Seasonally Adjusted:			
1. Without prior CNY adjustment		2.78	3.96
2. With prior CNY adjustment	Reciprocal factor methodology	2.27	2.54
3. With prior CNY adjustment	RegARIMA model	3.20	4.26
4. With prior CNY adjustment	**Directly adjusted from CIs**	**1.70**	**1.88**

S1 refers to the average month-on-month percentage change of the series.
S2 refers to the standard deviation of the month-on-month percentage change of the series.

Chart 10

Ratios of CIs to Yearly Average of CIs

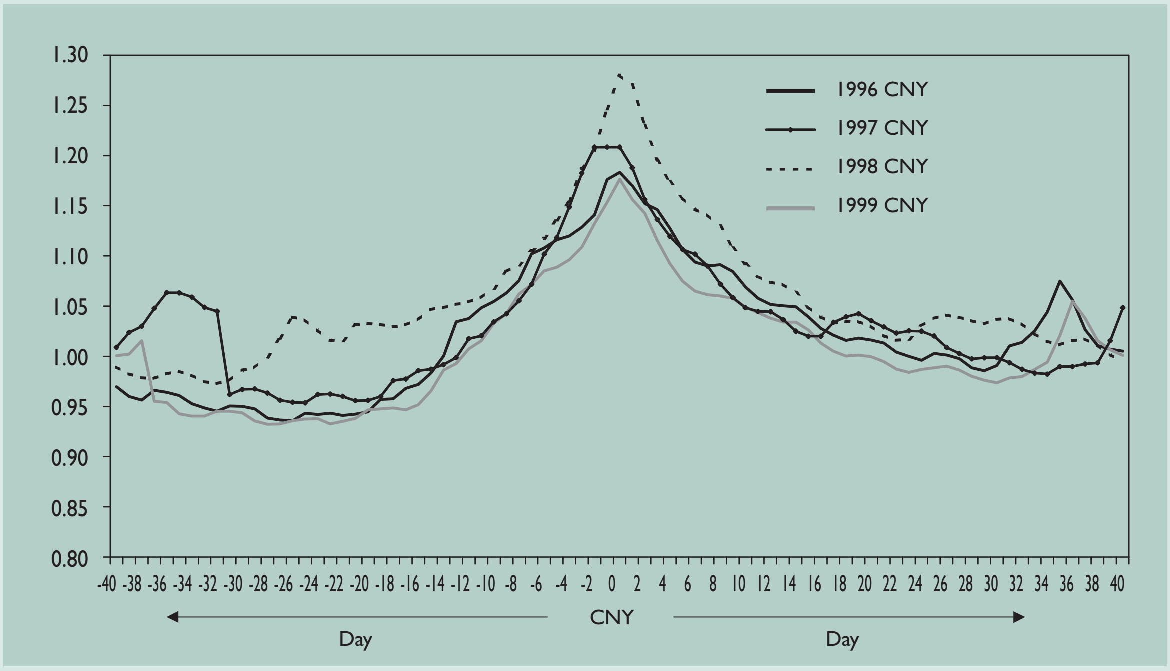
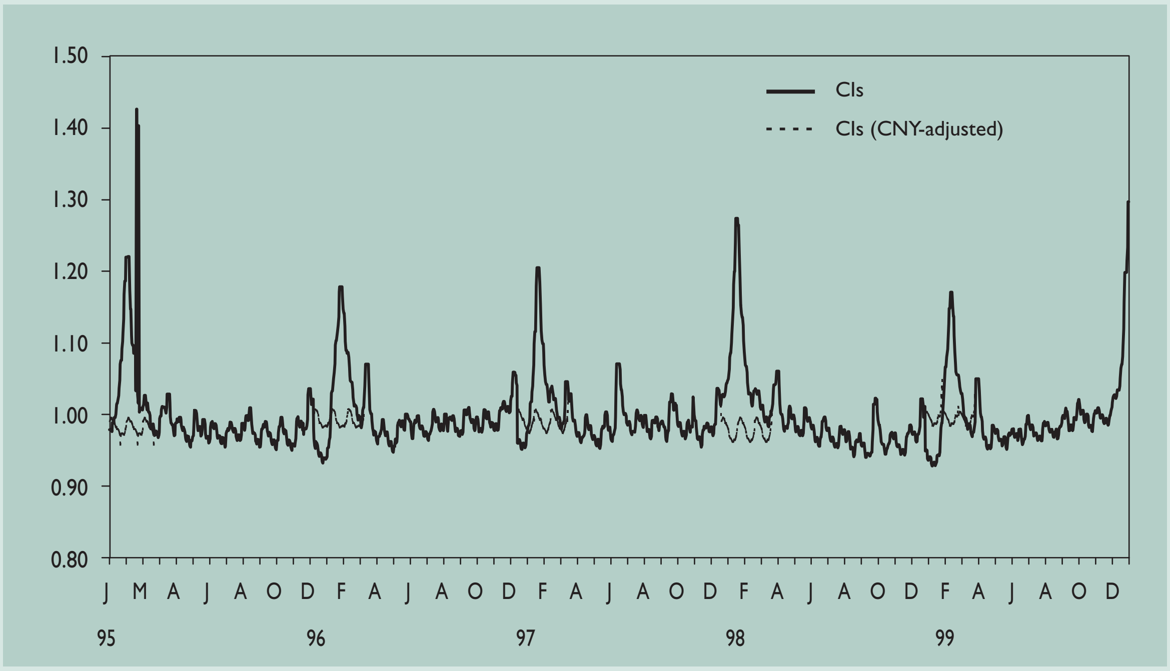


Chart 11

Ratios of CIs to Yearly Average of CIs



adjusted series. As a result, adjustments were made to pre-filter CNY influences and then the series was seasonally adjusted using the conventional X-12 procedures.

VII. Seasonally Adjusted HK$M1

Seasonally adjusted HK$M1 was derived from indirect adjustment method, as HK$M1 consists of currency held by the public and demand deposits. These two components were seasonally adjusted separately and then added to form seasonally adjusted HK$M1. Annex 5 compares the seasonally adjusted data series with the original series for HK$M1 and its components. A comparison of the unadjusted and deseasonalised growth rates is also shown in Table 5.

VIII. Publication Arrangements

As the above findings suggest the existence of seasonality in HK$M1 and its components, we plan to publish the seasonally adjusted data in the press release of monetary statistics starting from November. Seasonally adjusted data for these three series will also be made available in the December Monthly Statistical Bulletin when they are first issued.

Table 5

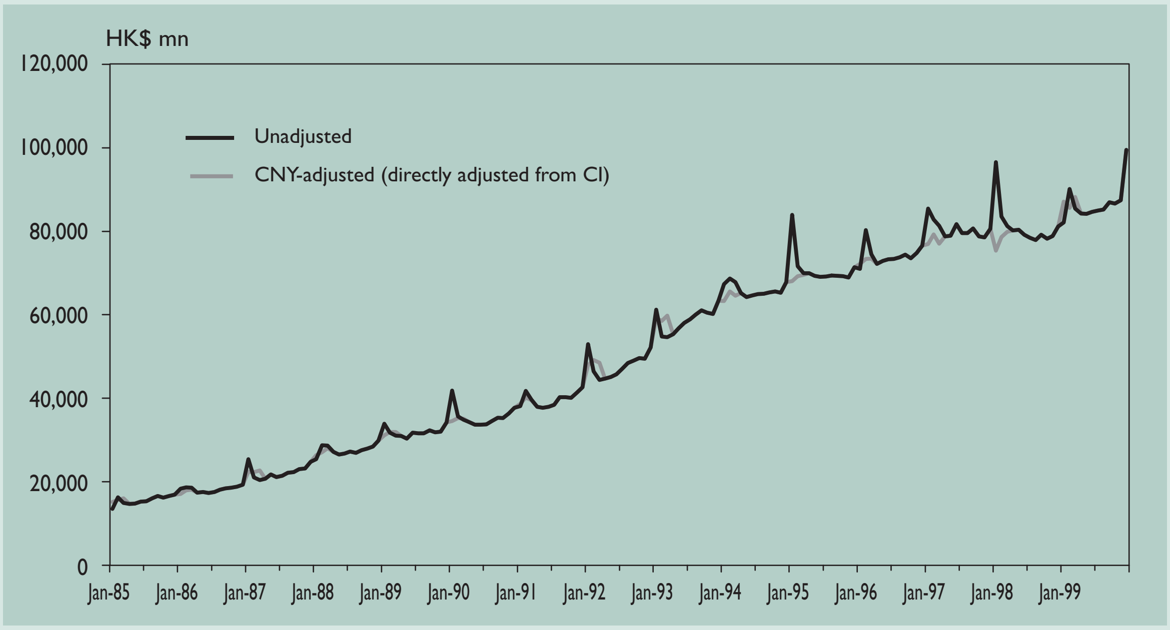
HK$M1 and Its Components (Percentage Change During the Month)

Year	Month	Currency Held by the Public		HK$ Demand Deposits		HK$M1	
		NSA	SA	NSA	SA	NSA	SA
1998	Jan	19.8	-0.6	-11.2	-13.0	2.1	-7.7
	Feb	-13.5	-3.7	3.8	6.5	-4.9	1.8
	Mar	-2.8	2.5	5.2	5.5	1.6	4.2
	Apr	-1.3	1.4	-0.7	-1.0	-0.9	0.1
	May	0.2	0.7	-10.4	-8.7	-5.8	-4.6
	Jun	-1.4	-1.3	-1.9	-2.3	-1.7	-1.9
	Jul	-1.0	-0.5	1.1	0.5	0.2	0.1
	Aug	-0.7	-0.2	-2.9	-1.2	-1.9	-0.7
	Sep	1.7	0.8	0.6	-1.5	1.1	-0.5
	Oct	-1.2	0.6	5.8	4.1	2.5	2.4
	Nov	0.8	0.6	5.5	9.6	3.3	5.5
	Dec	3.0	0.7	-3.1	-6.4	-0.4	-3.2
1999	Jan	1.1	6.5	-1.8	-3.7	-0.4	0.9
	Feb	9.8	-2.9	-6.7	-4.4	0.9	-3.7
	Mar	-5.2	3.9	8.3	8.2	1.5	6.1
	Apr	-1.5	-3.5	-0.4	-0.5	-0.9	-1.9
	May	-0.1	0.4	-2.0	0.0	-1.1	0.2
	Jun	0.6	0.7	3.7	3.5	2.2	2.2
	Jul	0.4	0.9	-4.0	-4.2	-1.9	-1.8
	Aug	0.2	0.9	4.3	5.5	2.4	3.3
	Sep	2.0	1.0	2.2	0.5	2.1	0.7
	Oct	-0.4	1.5	1.4	-0.1	0.6	0.6
	Nov	1.0	0.7	0.2	3.6	0.6	2.3
	Dec	13.8	-1.4	4.4	1.0	8.8	-0.1

NSA = Not seasonally adjusted
SA= Seasonally adjusted

Chart 12

Currency Held by the Public



For the seasonal adjustment process, an annual iterative cycle is suggested. Monthly seasonal factors will be computed at the end of each calendar year. This set of monthly seasonal factors will be used in the coming twelve months for seasonal adjustment purposes.

As regards the publication of revised series, it is recommended that seasonally adjusted data series for the previous twelve months be revised along with the release of December data, so as to facilitate month-on-month and year-on-year comparison of the seasonally adjusted series. More frequent revision of data may lead to public confusion. This revision schedule is widely adopted by other central banks.

IX. Conclusions

The findings of this paper are summarised as follows:

- At the aggregate level, HK$M1 exhibits a significant seasonal pattern, but there is no strong evidence of seasonality in broad money (HK$M2 and HK$M3).

- Within HK$M1, there is pronounced seasonality in currency held by the public and demand deposits. The former is associated with the Chinese New Year effect.

- The shifting nature of the CNY effect, combined with the characteristics of monetary statistics, suggested that conventional pre-filtering techniques did not work well. More robust estimates of the CNY effect were obtained using daily information on CIs.

- The seasonally adjusted HK$M1 was formed from the sum of seasonally adjusted currency held by the public and demand deposits.

- Prepared by the Economic Research Division

A REGARIMA MODEL

A general regARIMA model is as follows.

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D z_t = \theta(B)\Theta(B^s)a_t \qquad (1)$$

where B is the backshift operator $(Bz_t = z_{t-1})$, s is the seasonal period, $\phi(B)$ is the non-seasonal autoregressive (AR) operator, $\Phi(B^s)$ is the seasonal AR operator, $\theta(B)$ is the non-seasonal moving average (MA) operator, $\Theta(B^s)$ is the seasonal MA operator, and the $a_t s$ with mean zero and variance σ^2 (white noise). The $(1-B)^d(1-B^s)^D$ implies non-seasonal differencing of order d and seasonal differencing of order D. If d=D=0 (no differencing), it is common to replace z_t in (1) by deviation from mean, that is, by $z_t - \mu$ where $\mu = E[z_t]$. A useful extension of ARIMA models results from the use of a time-varying mean function modelled via linear regression effects. More explicitly, suppose a liner regression equation for a time series y_t is written as:

$$y_t = \Sigma_i B_i x_{it} + z_t , \qquad (2)$$

where x_{it} are regression variables observed concurrently with y_t, the B_i are coefficients, and $z_t = y_t - \Sigma B_i x_{it}$, is the time series of regression errors, which are assumed to follow the ARIMA in equation 1. The expressions (1) and (2) taken together define the general regARIMA model incorporated in the X-12 ARIMA programme. Combining (1) and (2), the model can be written in a single equation as

$$\phi(B)\Phi(B^s)(1-B)^d(1-B^s)^D (y_t - \Sigma B_i x_{it}) = \theta(B)\Theta(B^s)a_t . \qquad (3)$$

The regARIMA model (3) implies that, first, the regression effects are subtracted from y_t to get the zero mean series z_t. Then the error series z_t is differenced to get a stationary series, say w_t, and w_t is then assumed to follow the stationary ARIMA model, $\phi(B)\Phi(B^s)w_t = \theta(B)\Theta(B^s)a_t$. Another way to write the regARIMA model (3) is:

$$(1-B)^d(1-B^s)^D y_t = \Sigma B_i (1-B)^d(1-B^s)^D x_{it} + w_t . \qquad (4)$$

Equation (4) emphasises that the regression variables x_{it} in the regression model, as well as the series y_t, are differenced by the ARIMA model differencing operator $(1-B)^d(1-B^s)^D$.

OUTLIERS IN MONETARY AGGREGATES SERIES DETECTED BY X-12 ARIMA PROGRAMME

Demand Deposits	HK$M1	HK$M2	HK$M3
Apr 86	Apr 86	Apr 86	Apr 86
Sep 92	Sep 92	Oct 92	Oct 92
Oct 92	Oct 92	Oct 93	Oct 93
Oct 93	Oct 93	Nov 93	Nov 93
Aug 95	Aug 95	Jan 94	Jan 94

Sep 92

The share flotation of the M.C. Packaging (HK) Ltd., with total application monies amounted to HK$18.1 billion, distorted the demand deposits figure.

Oct 92

Total application monies of HK$148.4 billion from the share flotation of the China Travel International Investment Limited was placed in demand deposits (HK$97 billion) and time deposits (HK$51 billion).

The surge in demand deposits, however, was partially offset by the refunding of the subscription monies of the M.C. Packaging (HK) Limited (HK$18.1 billion).

Oct 93

The flotations of the Maanshan Iron & Steel Company Limited and the International Bank of Asia Limited involved subscription monies totalling HK$81.9 billion placed partly as demand deposits and partly as time deposits.

Nov 93

Subscription monies amounting to HK$181.9 billion from the flotations of the Kunming Machine Tool Co. Ltd., the Esprit Asia Holdings Ltd. and the Consolidated Electric Power Asia Ltd. was placed as time deposits.

The increase in time deposits was partly offset by the refunding from the Maanshan Iron & Steel Co. Ltd. and the International Bank of Asia (HK$81.9 billion). The refunding was also the reason for a 29.8% mom drop in demand deposits.

Jan 94

The flotations of the Legend Holding Ltd. and the Van Shung Chong Holding Ltd. tied up subscription monies of HK$88.5 billion, which was placed partly as time deposits and partly as demand deposits.

Aug 95

Demand deposits rose 19.1%. But the figure was upwardly distorted to the extent that some cheques deposited on 31 August were credited to payees' accounts but were not debited from payers' accounts due to the typhoon on that day.

IRREGULAR COMPONENTS

Chart A3a

Currency Held by the Public (Irregular Components)

Chart A3b

Demand Deposits (Irregular Components)

Chart A3c

HK$M1 (Irregular Components)

SUMMARY OF ADJUSTMENT PROCEDURES FOR THE CERTIFICATES OF INDEBTEDNESS SERIES

An article on seasonality in the Exchange Fund was published in the *Quarterly Bulletin* in 1996. The study suggested apparent seasonality in the data on Certificates of Indebtedness (CI). In addition, the CI series is affected by the Chinese New Year holiday, which does not necessarily occur in the same month each year. The study used a commonly adopted method of "reciprocal pair" of seasonal factors to remove the Chinese New Year effect before seasonal adjustment.

The pair of factors refers to the irregular factor and a derived reciprocal factor of two consecutive months. The reasoning behind the use of such a pair of factors is that, after the seasonal component's effect has been accounted for, the holiday effect on one month (such as the effect of the Chinese New Year in January) will either net out in the same month or reverse in the following month (in February). For example, a 3% increase in one month will be balanced out by roughly a 6% decrease in the next month. At present, the same method is applied by the Economic Research Division to adjust for the Chinese New Year effect on retail sales and external trade data. The procedures are as follows.

1. Apply the *X-11* procedure to the unadjusted series;

2. obtain the series for January (I_{Jan}) from the series of irregular (I) component;

3. regress I_{Jan} on the absolute number of days between Chinese New Year and end-January (N_t), i.e., $I_{Jan} = \alpha + \beta N_t + \mu$;

4. obtain the fitted values (I^a_{Jan}) from the above regression;

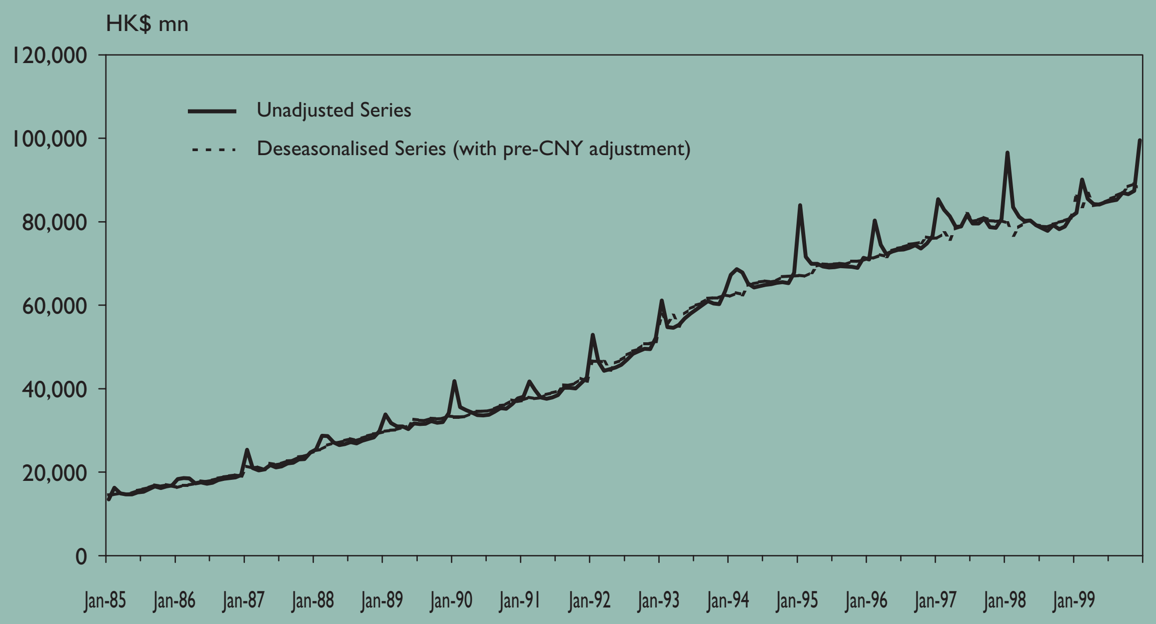
5. by forcing the holiday factors of January and February to add up to 200, the holiday factor for February is derived as $200 - I^a_{Jan}$;

6. the holiday adjusted values for January and February are estimated as
   $y^a_{Jan} = (y_{Jan} / I^a_{Jan})$
   $y^a_{Feb} = (y_{Feb} / (200\text{-}I^a_{Jan}))$;

7. finally, apply the *X-11* procedure to the holiday adjusted series to get the deseasonalised series.

UNADJUSTED AND SEASONALLY ADJUSTED SERIES

Chart A5a
Currency Held by the Public



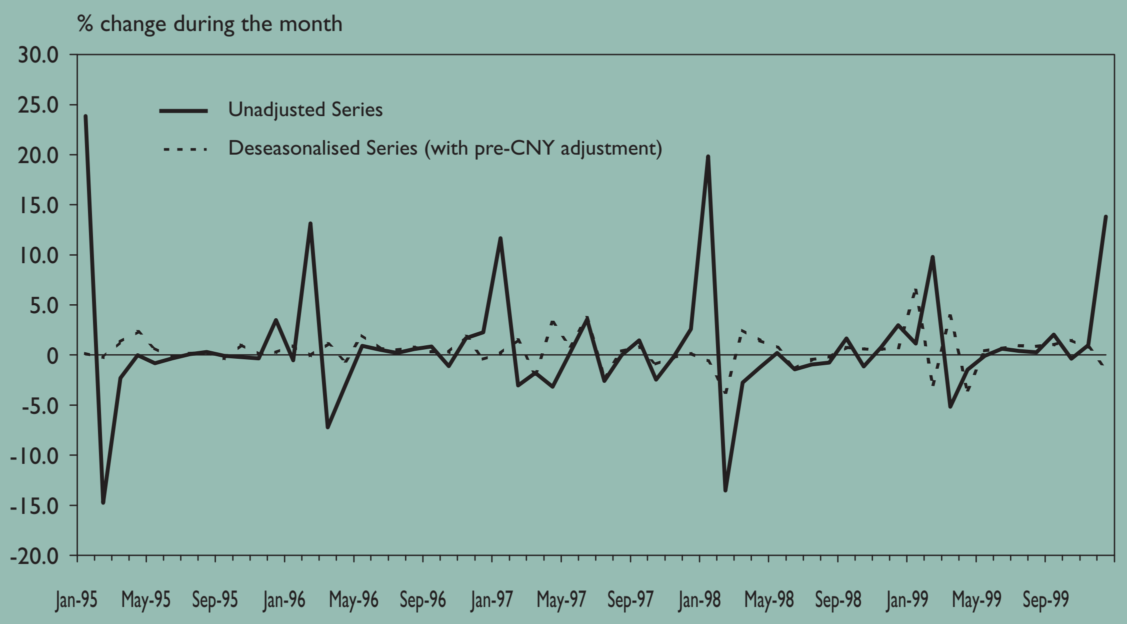
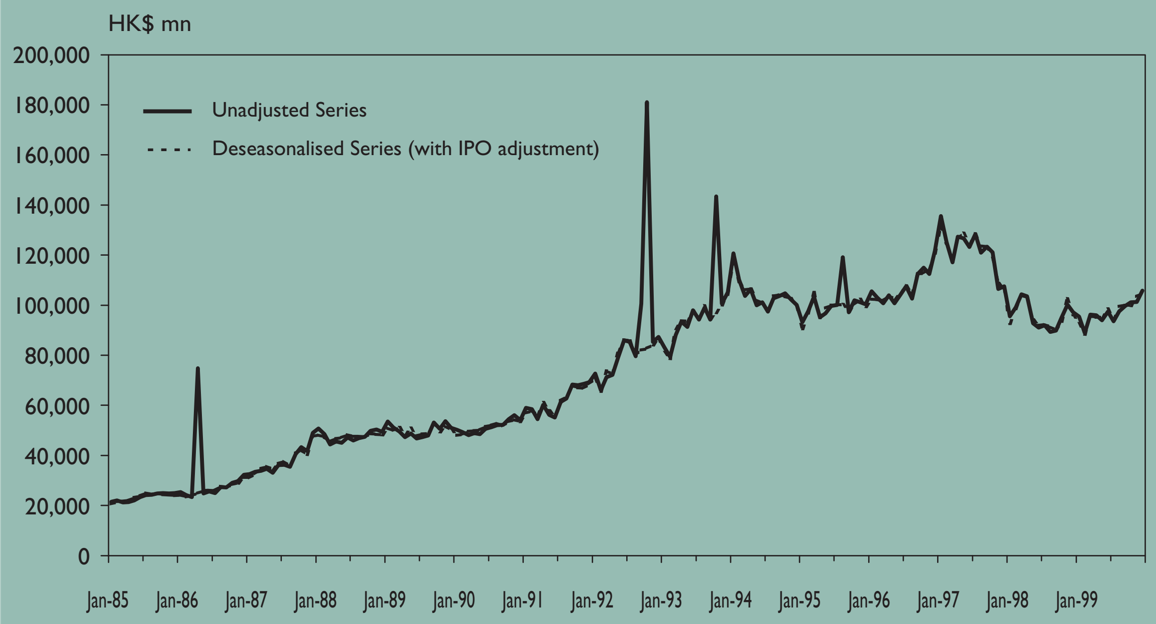


Chart A5b

Demand Deposits



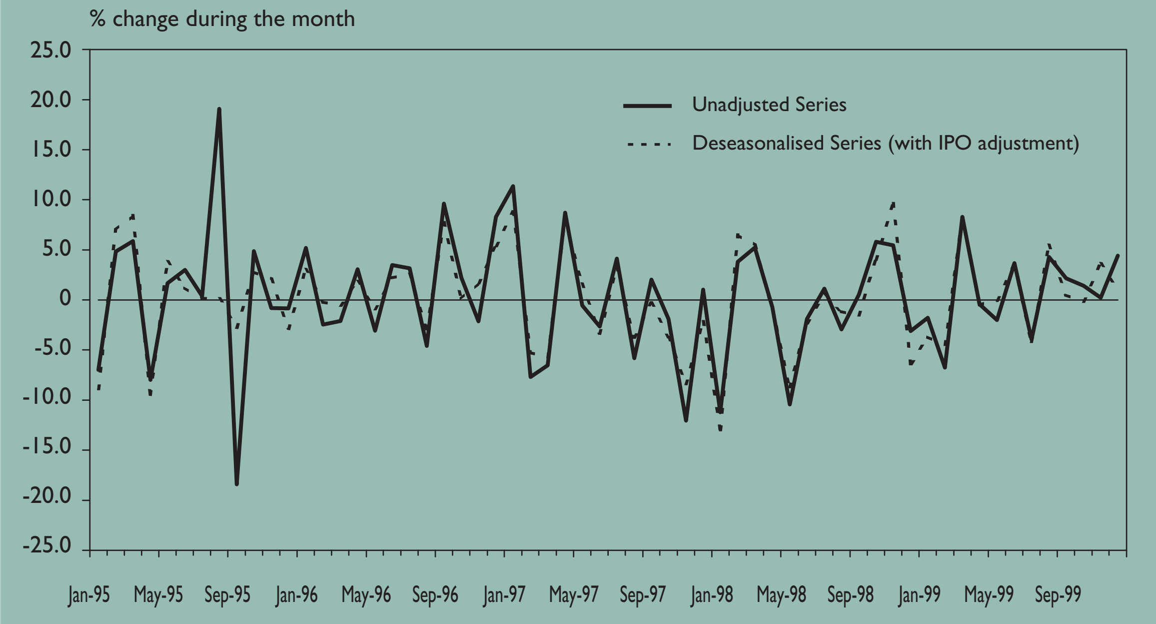
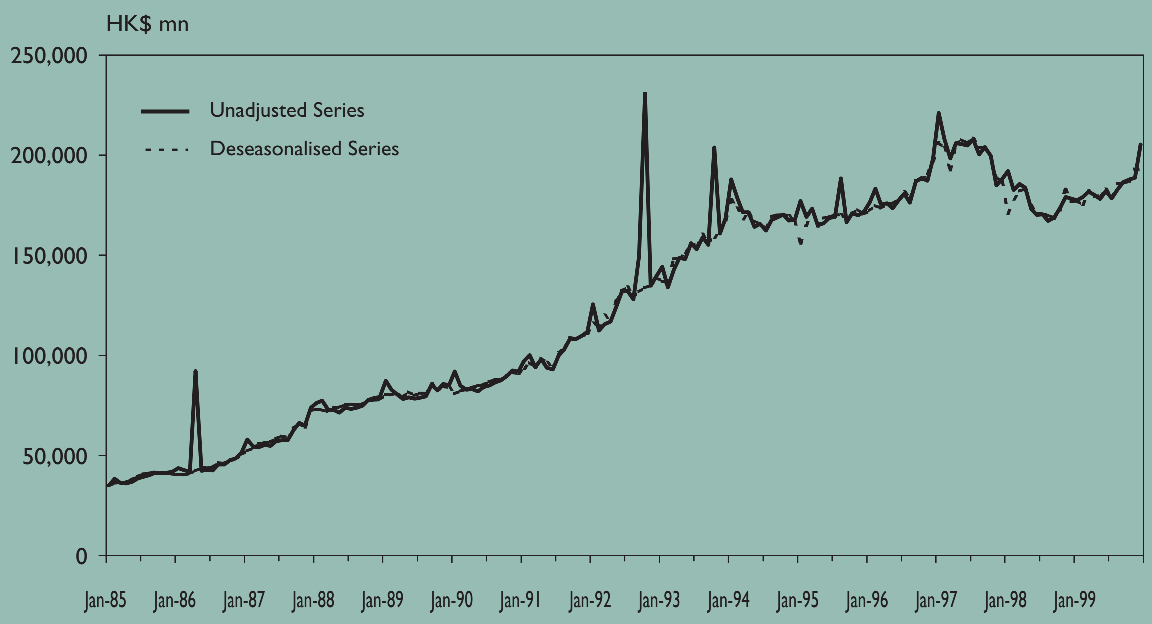
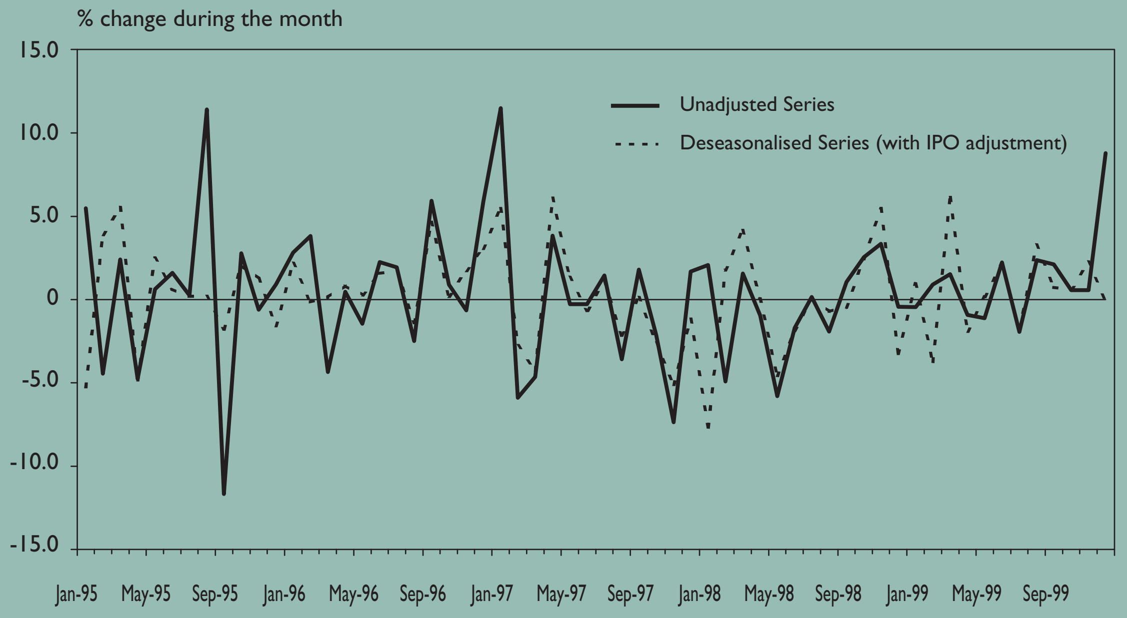


Chart A5c
HK$M1





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