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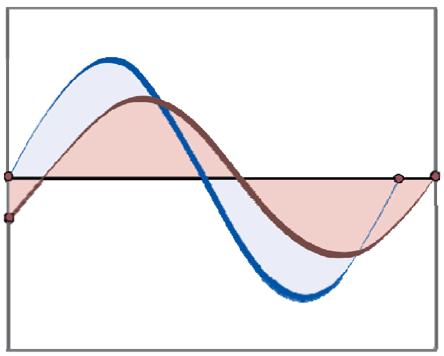

Seasonally Adjusting Economic Time Series in Trinidad and Tobago

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The Central Bank of Trinidad and Tobago (CBTT) has produced seasonally adjusted data since the early 1980's. Publication of a seasonally adjusted quarterly GDP Index continues to the present time, but the CBTT ceased production of seasonally adjusted monetary aggregates in 1992 due to technical challenges. In this context, the paper applies the two most commonly used seasonal adjustment software packages – the US Census Bureau X-12-ARIMA and the TRAMO/SEATS - to selected monetary and real economic time series for Trinidad and Tobago. The tests reveal significant seasonality in data sets for retail sales, cement sales, currency in circulation and demand deposits, among others. The paper recommends that, based on its wide range of diagnostic tests, the X-12 ARIMA program should be adopted for seasonal adjustment by the CBTT. It further recommends that seasonally adjusted monetary series should be published on a regular basis alongside the raw statistics.

JEL Classification Numbers: C22, C40, C54

Keywords: Seasonal Adjustment, X-12-ARIMA, Economic Time Series, Trinidad and Tobago.

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1. Introduction

Economic statistics are key inputs into economic policy-making, business cycle analysis, modeling and forecasting. However, high frequency statistics (e.g. quarterly GDP, retail sales, monetary aggregates, etc) are often characterized by seasonal fluctuations (regular, intra-year seasonal movements around annual trend paths) which can distort the underlying short and long-term movements of the series, and hinder a clear understanding of economic phenomena. Seasonal adjustment methods aim to remove seasonal and calendar influences to produce a clearer picture of the underlying behaviour of time series. This enables policymakers to distinguish and analyze the trend from an economic time series without being obscured by seasonal patterns.

In order for high frequency indicators to be useful for the formulation of policy, the aggregates must be presented in such a way as to reflect trends in economic activity. However, the presence of recurring seasonal patterns obscures their underlying behaviour and distorts short term analysis (i.e. quarter-on-quarter and month-on-month changes). For example, the Retail Sales Index for Trinidad and Tobago tends to peak during the fourth quarter due to Christmas-related demand and dips in the first quarter as demand declines following the Christmas festivities. If seasonally adjusted estimates are not available, changes in trend are typically judged by comparing the level or change in the latest period with the same period in the previous year (i.e. the year-on-year percentage changes). Seasonal adjustment of economic time series facilitates a better assessment of recent movements in economic activity. Quarter-on-quarter or month-on-month percentage changes using seasonal adjusted estimates have the added advantage of detecting turning points faster than the year-on-year changes.

Seasonal adjustment of economic time series by CBTT dates back to the late 1970's. The Bank was among the first official statistical agencies in the region to frequently publish seasonally adjusted numbers. However, CBTT seasonally adjusted data failed to attain widespread credability and acceptance because statisticians did not appreciate the of scope of the seasonal adjustment process[2]. While the Bank's publication of seasonally adjusted monetary series was discontinued in 1992, the Bank currently reports seasonally adjusted estimates of its Quarterly Gross Domestic Product (QGDP) Index at both the sectoral and aggregate levels.

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[2] See Clarke and Francis (1996).

The purpose of this paper is to re-examine the issue of seasonal adjustment of time series in Trinidad and Tobago and propose an appropriate seasonal adjustment program. In so doing, two widely used software programs are utilized to conduct tests on selected real economic time series and monetary aggregates.

This paper will proceed in section 2 with an explanation of the theory and methods of seasonal adjustment and the procedures involved. This will be followed by a review of various country experiences with seasonal adjustment techniques. Section 3 will explore the results and diagnostic tests of seasonally adjusting selected series in Trinidad and Tobago. Section 4 will conclude and give some policy recommendations.

2. Seasonal Adjustment – Theory, Methods and Software

i. Time Series Decomposition

Seasonal adjustment is the process of using analytical techniques to estimate and remove seasonal and calendar effects which obscure the long term trends of economic time series. Bell and Hillmer (1984) indicated that seasonal adjustment is done to simplify data so that they may be more easily interpreted by statistically unsophisticated users without a significant loss of information. Bersales (2007) noted that seasonal adjustment identifies the different components of the time series thereby reflecting its true behavior. Therefore, seasonally adjusted time series facilitate a better assessment of their recent movements, including the timely identification of turning points.

The analysis of time series and their components dates back to the 18th and 19th centuries.[3] Time series can be disaggregated into three independent non observed component series: the seasonal (S), trend-cycle (TC), and the irregular (I) components.

The seasonal component (S) can be separated into two sub-components; seasonality and calendar effects. Seasonality represents intra-year fluctuations that are more or less stable year after year in the context of timing, direction and magnitude. In the Trinidad and Tobago context, some economic time series such as retail sales and money supply normally peak during the fourth quarter (due to the Christmas festivities that lead to greater volume of sales and use of credit) and dip during the first quarter. Calendar effects, for example the trading day (TD) and Easter (E) effects, represent regular variations such as the number of trading/working days, moving holidays (Easter, Eid, Divali, etc.) as well as other variations that are not regular in annual timing.

The trend-cycle component (TC) is the long-term movement in the data or cyclical movements having a longer periodicity than one year. It captures the long term upward or downward movements of the time series due to influences such as population growth, price inflation and general economic development (Bersales, 2007). The irregular component (I) is the residual after the trend-cycle and seasonal components are extracted from the original series. It comprises the random fluctuations of short-term movements of the time series. In other words, the Irregular fluctuations may result from a combination of unpredictable or unexpected factors including sampling errors, non-sampling errors, unseasonable weather, natural disasters and strikes. Seasonal adjustment methods eliminate the seasonal component and produce series that exhibit their true underlying trends and short term movements.

In order to seasonally adjust a time series, outliers also have to be detected and removed. These are data points which do not fit the general pattern of the trend and seasonal component. Outliers can be categorized as either additive or level shift outliers. An additive outlier is an extreme value that falls out of the general trend of the series. This is a one-off effect that may result from a strike or bad weather. Level shift outliers can result from structural

[3] See Busby and Ballot (1847)

movements including legislative changes, the closure of a major company, etc. Outliers need to be removed before carrying out seasonal adjustment since they affect the quality of forecasts and the seasonal and trend components (particularly in methods that use moving averages). Outliers due to data errors should be corrected in the raw time series; others should be excluded before seasonal adjustment is performed and then reintroduced in the different components.

ii. Additive and Multiplicative Decomposition Models

The three components are assumed to have a certain relationship. The most frequently specified relationships are the additive and multiplicative models. Assuming that Yt denotes a seasonally unadjusted time series, an additive model is used when the components are related additively:

$Y_t = TC_t + St + I_t$

Similarly, a multiplicative model is specified when the components are linked multiplicatively:

$Y_t = TC_t \times S_t \times I_t$

For a multiplicative model, the absolute variation due to the seasonal component increases as the underlying trend rises, while in the additive model, the absolute variation due to the seasonal component is independent of the level of the underlying trend. The additive model is used if the seasonal effects are the same every year. The trend of the series changes but the magnitude of the seasonal fluctuations remains approximately the same. In other words the three components that make up the time series are independent of each other. Findley et al (1998) noted that multiplicative decomposition is usually appropriate for series of positive values (sales, shipments, exports, etc.) in which the size of the seasonal oscillations increases with the level or trend of the series, a characteristic of most seasonal macroeconomic time series. Most studies also confirm that the majority of economic time series are typically multiplicative models. The Retail Sales Index for Trinidad and Tobago is an economic time series that has characteristics of a multiplicative model (Section III, Box 2).

iii. Direct versus Indirect Seasonal Adjustments

Several time series are aggregates of component series (for example, total exports is the sum of exports to all trading partners and GDP is an aggregate of value added in all economic sectors). Seasonally adjusted aggregate series can be derived using either the indirect or direct methods. Indirect seasonal adjustment[4] is the process of seasonally adjusting the component series and then aggregating the adjusted components to derive the seasonally adjusted

[4] A joint Task Force, established by Eurostat and the ECB in 2001, found that eight out of twelve countries in the EU compile seasonally adjusted totals through the indirect method via aggregation of sub-components of the output, expenditure or income side. The preference to avoid statistical discrepancies between the adjusted aggregates and the components was the main reason for most countries using the indirect method.

aggregate series. Direct seasonal adjustment involves aggregating the component series (i.e. the unadjusted series) and seasonally adjusting the total. As Dagum (1979) noted, the use of direct or indirect adjustment depends on the set of series in question.

Consider a series X_t, which is the aggregate of six component series:

$$X_{i,t} = TC_{i,t} + S_{i,t} + I_{i,t}$$

i= 1, 2,…,6

$$X_t = \sum_{i=1}^{6} w_i X_{i,t}$$

Where w_i is the weight for component i.

Two different seasonally adjusted series, A_t, can be derived:

1. A_t^D= The directly adjusted aggregate of the six components (i.e. Xt).
2. A_t^I =The aggregate of the seasonally adjusted components.

$$A_t^I = \sum_{i=1}^{6} w_i A_{i,t}$$

Where A_t^I is the indirect seasonal adjustment of X_t and $A_{i,t}$ is the adjusted components.

Direct seasonal adjustment results in the loss of additivity (i.e. the seasonally adjusted aggregate series will not equal the summation of its seasonally adjusted components). However, direct seasonal adjustment does have its advantages, and is generally applied where the preservation of additivity is less important. Direct adjustment is usually appropriate if the component series exhibit similar seasonal patterns.

In contrast, indirect adjustment preserves additivity (i.e. the seasonally adjusted aggregate is the sum of the seasonally adjusted components). Empirical studies suggest that when the component series have distinct seasonal patterns, indirect adjustment is preferable. Atuk and Ural (2002) indicated that the indirect approach should be used when sources of data components are different and when components have different working day/trading effects while direct seasonal adjustment is preferred when components are highly correlated. For these reasons, series such as quarterly GDP should be indirectly adjusted since its components (sectors) have distinct seasonal patterns and data sources. Most countries, including Singapore, Denmark, Philippines, Iceland , European and OECD countries, apply indirect seasonal adjustment to quarterly GDP.

However, the necessary pre-conditions do not necessarily support a particular approach. For example, monetary series collected from different data sources may have similar seasonal patterns (i.e. highly correlated) which suggest that direct seasonal adjustment may be appropriate.

iv. Seasonal Adjustment Methods

Year-On-Year Growth Rates

The simplest approach that is used to remove normal seasonal movements from time series is the calculation of year-on-year changes (i.e. the percentage change between two equivalent periods of two successive years). However, the year-on-year changes are slow to detect turning points and reflect irregular events affecting the data in the current period and the corresponding period of the previous year. Year-on-year changes also involve comparison of values that include developments over the preceding twelve month period. As a consequence, year-on-year rates of change do not capture recent trends in data and are inadequate for business-cycle analysis (Quarterly National Accounts Manual, 2001; Bersales, 2007). Quarter-on-quarter comparison of seasonally adjusted data provides a more meaningful comparison over the short term and is more useful for the early detection of turning points.

The US Census Bureau X-12-ARIMA and TRAMO/SEATS[5]

There are several known seasonal adjustment software packages, but the US Census Bureau X-12-ARIMA (Autoregressive Integrated Moving Average) and the TRAMO/SEATS (Time series Regression with ARIMA noise, Missing observations, and Outliers/Signal Extraction in ARIMA Time Series) programs are the most widely used and will be discussed in this paper[6].

The methods utilized by the X-12-ARIMA program culminated from a sequence of variants of moving average methods. The first seasonal adjustment methodology was created by Macauley (1930), which used the ratio-to-moving average method. This method was commonly referred to as "Classical Decomposition" and laid the fundamentals for modern day approaches including the Census Bureau X-12-ARIMA method.

In 1954, the US Census Bureau introduced the first computer program (using the Census I method) for seasonally adjusting economic time series. This made the large-scale application of the ratio-to-moving-average method possible for the first time. In 1955, the original Census Bureau program was replaced with a revised procedure called

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[5] Seasonal adjustment software (e.g. X-12-ARIMA, TRAMO/SEATS) uses specific recognized procedures and algorithms (e.g. ARIMA modeling, moving averages) to decompose time series into its components. In this paper, the term “program” will be used strictly in reference to the software packages used for seasonal adjustment, while the term “method” will be used when describing the adjustment procedures and techniques utilized by the programs.

[6] Less common methods include the “Berlin Procedure” (BV) that is used in Germany and applies a moving (local) regression model approach which was introduced by at the Berlin Technical University and the German Institute for Economic Research (DIW) and the Dainties method which is based on the basic decomposition model to trend, seasonal and irregular components but only provides the user with the seasonally adjusted series.

the Census Method II. Its widespead use was due largely to important new features, including a variety of moving averages for estimating evolving trend and seasonal components, refined asymmetric moving averages for use near the ends of the time series, and methods for estimating trading day effects.

After extensive research, the US Census Bureau introduced the Census X-11[7] program in 1965, the most widely used software until the 1980's. However, as Ural and Atuk (2002) noted, this program contained several imitations that led to the search for an improved methodology:

- The method utilized by the software was not based on any statistical model.
- The moving average filtering procedure implicitly assumed that all effects except the seasonal effect were approximately symmetrically distributed around their expected value and thus could be fully eliminated by using the centered moving average filter.
- The loss of observations (resulting from the moving average method) caused the seasonal effect to be underestimated.
- There was incomplete removal of seasonality when the economic time series exhibited stochastic seasonality.

Following the work of Box and Jenkins in the 1970's on autoregressive moving averages, the Census X11-ARIMA program was established by Dagum (1980) of Statistics Canada, with several improvements over the Census Bureau's X-11 program. These included the program's ability to extend time series with forecasts and backcasts (using ARIMA models) prior to seasonal adjustment,[8] more systematic and focused diagnostics for assessing the quality of its seasonal adjustments, and diagnostics for comparing indirect and direct seasonal adjustments of aggregated series.

The US Census Bureau X-12-ARIMA program (the latest version that uses moving average filters) introduced by the US Census Bureau in 1997, was an advancement of the X11-ARIMA program, featuring new diagnostics and modeling capabilities (Findley et al, 1998). The main improvement is the pre-treatment of data by means of an extensive set of time series model building facilities built into the sub-programme in order to fit regression ARIMA models (regARIMA models). RegARIMA models are linear regression models with ARIMA errors. The regARIMA sub-program provides forecasts, backcasts, and pre-adjustments for various effects (using regression variables) before seasonal adjustments are performed. Forecasting and back-casting provide a longer span of data to input into the seasonal adjustment process, leading to a higher quality of seasonal adjustment, particularly at the end of the series. Adjustments for other effects including calendar and outlier effects (via the use of regression variables which

[7] This program was used by Farrell and Chow (1980) to seasonally adjust monetary and production time series.
[8] The use of forecasts and back-casts extensions results in initial seasonal adjustments whose revisions are smaller, on average, when they are recalculated after future data become available.

are mainly dummy variables), make the seasonal adjustments more robust by preventing them from distorting the subsequent estimation of seasonality (Appendix 2, Box 2.1). Supplementary statistical diagnostics for assessing the appropriateness of the model selected are also included (e.g. revision history and sliding spans diagnostic analysis). This method has attained widespread use with most countries, including Singapore and the OECD countries.

Another popular software package is the TRAMO/SEATS program, developed by Victor Gomez and Augustine Maravall at the Bank of Spain (1997). This program uses ARIMA models as the basis for seasonal adjustment. It is a complete companion program which automatically identifies ARIMA models, outliers and other components. Like the regARIMA modeling in the X-12-ARIMA program, TRAMO[9] is used to pre-adjust a series by using time-series regression models to forecast and backcast input data and detect and correct for outliers, calendar effects, missing observations, etc. The pre-adjusted series is then seasonally adjusted by SEATS. SEATS is a program which estimates and forecasts the trend-cycle, seasonal and irregular components of a time series using ARIMA based signal extraction techniques with filters derived from an ARIMA-type time series model that describes the behavior of the series to tailor seasonal and trend filters to the series.

v. Procedure and Diagnostics of Seasonal Adjustment[10]

Prior to the adjustment process, the user needs to have extensive knowledge of the time series in terms of measurement, special events affecting the series, etc. The process of seasonal adjustment begins with the informal and formal testing procedures for seasonality in time series. The informal method involves visual inspection of the raw data to aid in the identification of seasonal patterns, while the formal approach involves the use of statistical tests.

The X-12-ARIMA program provides two statistical tests (the F-test and the Kruskal-Wallis Chi-Square test) for the presence of seasonality assuming stable seasonality (seasonal effects that do not alter significantly in the same period each year throughout the time span under study) and an F test for moving seasonality (a form of seasonality that accounts for the variability in the seasonal component of a time series from year to year). Moreover, the X-12-ARIMA program provides a combined test for identifiable seasonality. This test is a joint test of the F test, Kruskal Wallis Chi Square test and the F test for moving seasonality. At this stage, if identifiable seasonality is not present, the series should not be seasonally adjusted.

The most fundamental requirement of a seasonally adjusted series is the absence of residual seasonality (estimable seasonal affects in the seasonally adjusted series). Unlike the TRAMO/SEATS program, the X-12-ARIMA program provides an F test for residual seasonality. For aggregate series, the absence of residual seasonality among the adjusted component series does not guarantee the absence of residual seasonality in the adjusted aggregate series.

[9] For a comparison of the TRAMO/SEATS and X-12-ARIMA programs, see European Central Bank (2000).
[10] This paper will utilize the diagnostic tests of the X-12-ARIMA program since the TRAMO/SEATS program lacks diagnostics.

This may occur as a result of inappropriate ARIMA models or adjustment procedures chosen when adjusting the component series. Hood (2007), indicated that residual seasonality can be removed by reducing the span of the data used for seasonal adjustment or by changing the seasonal filters.

Another measure that is closely linked to residual seasonality is idempotency. Theoretically, the absence of residual seasonality in an adjusted series implies that application of a seasonal adjustment method to an already adjusted series should leave that series unchanged. In addition, idempotency can be used to identify between competing seasonal adjustment methods. The statistic used to test for idempotency (ID) is calculated as follows:

$$ID = \frac{100}{12n}\sum_{i=1}^{12}\sum_{j=1}^{n}\frac{\left|S_{ij}^{sc} - S_{ij-1}^{sc}\right|}{y_{ij}^{sc}}$$

Where: y_{ij}^{sc} = seasonally adjusted series

S_{ij}^{sc} = estimated seasonal component

n = number of years in the sample period

Idempotency exists when ID equals zero.

Once the absence of residual seasonality has been established, it is important to look at other diagnostics of quality seasonal adjustment. For this purpose, the X-12-ARIMA program computes a wide range of diagnostic tests including the "monitoring and quality assessment statistics"[11] (Appendix 1, Table 1.1), sliding spans analysis and revision history diagnostics.

The monitoring and quality assessment statistics include tests for the amount of moving seasonality relative to stable seasonality, the size of the fluctuations in the seasonal component throughout the series, etc. These naturally affect the reliability of the seasonal adjustment estimates.

The sliding spans analysis attempts to quantify the stability of the seasonal adjustment process and hence the suitability of seasonal adjustment for a given series. The sliding spans diagnostic works by seasonally adjusting at most four overlapping spans of the original series. The program selects span lengths which vary in accordance with the seasonal moving averages, the length of the series and whether the data are monthly or quarterly. Where the spans overlap, the program compares the seasonal factors, month-on-month and year-on-year percentage changes in each span for each data point. The program then computes the proportion of data points in the series, where two or more spans overlap, that qualifies as unstable. When the series fail either of these diagnostics, seasonal adjustment is not recommended.

[11] See Hungarian Central Statistical Office (2007).

In addition, the X-12-ARIMA program provides a revision history analysis. Generally, a seasonal adjustment method which leads to smaller revisions as data becomes available is preferred to methods with larger revisions. This diagnostic is normally used to choose among competing seasonal adjustment methods (e.g. direct and indirect seasonal adjustment).

In contrast, the TRAMO/SEATS[12] program lacks diagnostics to test for residual seasonality and to assess the quality of the adjustment, which implies that there is limited scope for comparing the performance of both programs.

vi. Seasonal Adjustment Programs: Selected Countries

The X-12-ARIMA and the TRAMO/SEATS programs have attained widespread use. Table 1 below highlights the extensive use of the two seasonal adjustment programs.

Table 1
Seasonal Adjustment Programs used by Selected Countries

Countries/ Institutions	Seasonal Adjustment Programs
United States/ US Census Bureau	X-12 -ARIMA
Canada/ Statistics Canada	X-11- ARIMA
Spain/ Bank of Spain	TRAMO/SEATS
Denmark/ Statistics Denmark	X-12 -ARIMA
England/ Bank of England	X-12 -ARIMA
Hong Kong/ Hong Kong Monetary Authority	X-12 -ARIMA
Japan/ Bank of Japan	X-12 -ARIMA
New Zealand/ Statistics New Zealand	X-12 -ARIMA
OECD	X-12 -ARIMA
The World Bank	X-12 -ARIMA
Turkey/ Central Bank of Turkey	X-12 -ARIMA & TRAMO/SEATS
United Kingdom/ Office of National Statistics	X-11 -ARIMA
Eurostat	TRAMO/SEATS

[12] See Hood and Findley (2000).

In 2006, the Hungarian Central Statistical Office surveyed 32 countries[13] (Table 2).

Table 2
Seasonal Adjustment Programs

Region	Seasonal Adjustment Programs			
	Tramo/seats	X-11	X-12	Other
EU-15	10	5	9	1
NMS-12	12	1	3	1
Non-EU	3	0	4	0
Total	25	6	16	2
Percentage (%)	81%	19%	52%	6%

Source: Central Statistical Offices of Hungary.

The results showed that 81% of the respondent NSIs (National Statistical Institutes) use some version of TRAMO/SEATS as a seasonal adjustment program. The X-12-ARIMA program took 52 per cent of the share of the total market, while the use of X11-ARIMA acquired 19 per cent of the share of the total market.

With the popularity of the X-12-ARIMA and the TRAMO/SEATS programs, several studies have emerged in an attempt to examine the performance of both programs. Atuk and Ural (2002) established that the TRAMO/SEATS program performed better than the X-12-ARIMA program on the seasonal adjustment of monetary aggregates in Turkey. However, Hood & Findley (1999) found contrasting results from seasonally adjusting series with the X-12-ARIMA and the TRAMO/SEATS programs. They found more evidence of residual seasonality among the series that were adjusted using the TRAMO/SEATS program when compared to the series that were adjusted using the X-12-ARIMA program. In particular, they found residual seasonality when they summed the TRAMO/SEATS adjusted component series to derive the indirect adjusted aggregate series while there was no residual seasonality in the indirect adjusted aggregate series with X-12-ARIMA. Hood & Findley (1999) also found that diagnostics from TRAMO/SEATS were sometimes misleading when identifying series that should not be adjusted and concluded that the diagnostics from X-12-ARIMA were better for this purpose. In addition, they identified that the TRAMO and SEATS are lacking in diagnostics while that the X-12-ARIMA has many features that make it easy to perform seasonal adjustment for a large number of series, a variety of diagnostics to test for a variety of problems in series, different types of output and diagnostic files and the ability to customize output files and log files.

vii. Concurrent Versus Forward Factors

Revisions of seasonally adjusted data can result from revisions to raw data, the availability of new data or an update to the seasonal estimation. The revisions to seasonally adjusted series can be carried out as soon as a new

[13] The 15 old EU Member States (EU-15), 12 new Member States (NMS-12) including Bulgaria and Romania which joined the EU in 2007 and the countries (Croatia, Iceland, Norway, Switzerland and Turkey) which are not Members of the EU.

observation becomes available (concurrent adjustment). Alternatively, seasonal factors and seasonally adjusted series can be projected on predetermined longer intervals such as a year (forward factor adjustment) to derive forecasted seasonally adjusted data (Atuk and Ural, 2002). When full year data are available, seasonal adjustment is performed and revisions are made. From a theoretical viewpoint, concurrent adjustment is preferred as seasonally adjusted estimates incorporate the most recent data or information but from a practical point of view, users may prefer stable seasonally adjusted estimates (i.e. forward factor adjustment). For popular series that attract major attention (e.g. quarterly GDP), the use of forward factor adjustment can be justified.

viii. Seasonal patterns in Economic Time Series

Real sector series, including quarterly GDP, retail sales and industrial indices, normally exhibit clear seasonal patterns. Specifically, these series tend to increase during fourth quarters due to the Christmas related demand followed by a dip in the first quarters due to lower expenditure subsequent to the Christmas season. In addition, real sector series are also influenced by other calendar effects including the moving holiday (e.g. Easter) and trading day effects. For example, the Easter holiday (in March or April) and months with more trading days are likely to generate higher sales.

Similarly, monetary aggregates are affected by several seasonal factors. Holidays precipitate a higher volume of sales and greater use of credit. For example, the public tends to hold a greater amount of cash ahead of and around the Christmas period to faciliatate the higher number of retail transactions. Income and corporate tax payments generate large transfers from individuals and businesses to government around certain dates. The government also distributes refunds to taxpayers because of over withholding while many paychecks are issued at the end of the week or the month, and this practice affects the timing of other payments (Pierce & Cleveland, 1981). In addition, people typically cash paychecks or withdraw from ATMs on weekends, leading to more active cash on Mondays relative to Fridays. This can complicate a direct comparison of money supply figures from one month to the next. The abovementioned factors call for seasonal adjustment in order to more clearly understand quarterly or higher frequency changes in economic time series.

3. Empirical Results

This section explores the results and diagnostics of seasonally adjusting selected real economic time series and monetary aggregates in trinidad and tobago using the X-12-ARIMA and the TRAMO/SEATS programs. The lack of diagnostics in the TRAMO/SEATS program limited the prospects for comparing the performance of the two seasonal adjustment programs to the residual seasonality and idempotency tests. All adjusted series from the TRAMO/SEATS program were input into the X-12-ARIMA program to test for seasonality (i.e. residual seasonality). Other diagnostics, including stability diagnostics and monitoring and quality and assessment statistics, were also explored for the adjusted series from the X-12-ARIMA program.

The economic time series[14] for the period 2000 to 2010 that have been selected for adjustment are:

1. Real Sector
    - QGDP Index – non-energy sector (QGDP Index)
    - Local sales of cement (LSC).
    - Retail Sales Index (RSI).
    - Private motor vehicles sales (PMVS).
    - Domestic production Index (DPI).[15]

2. Monetary Aggregates

    The monetary aggregates and their descriptions are presented in Table 3 below.

Table 3
Monetary Aggregates and Description

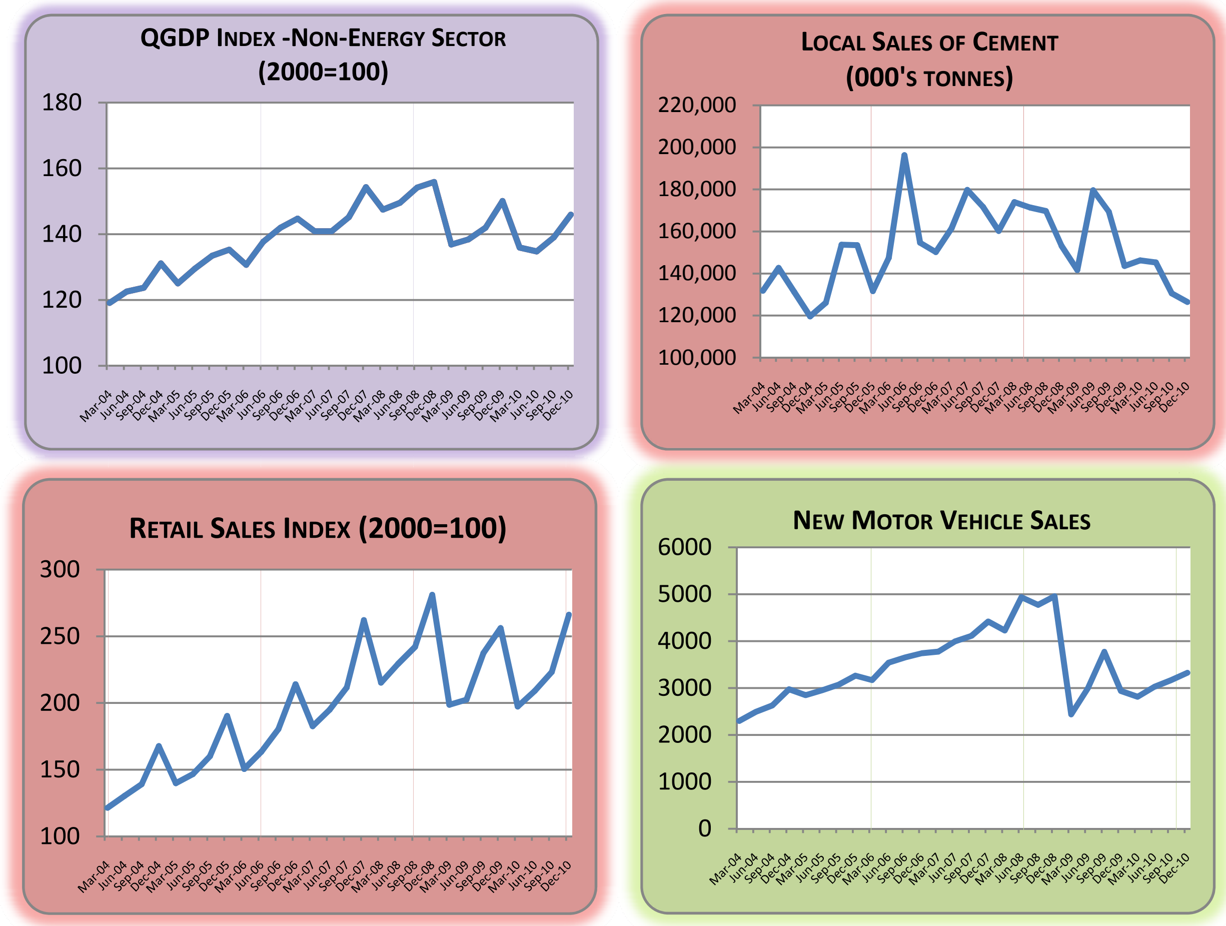
Monetary Series	Description
Base money (M-0)	Currency in Active Circulation (CAC) + Commercial Banks' Deposits at Central Bank (CBD).
Narrow money supply (M-1A)	Currency in Active Circulation (CAC) + Demand Deposits (DD).
Money supply (M-1C)	M1A + Saving Deposits (SD)
Broad money supply (M-2).	M-IC + Time Deposits (TD)
Broad money supply (M-2)*	M2 + Commercial Banks Foreign Currency Deposits (CBFCD)
Broad money supply (M-3)	M-2 +Non-Bank Financial Institutions (NBFI) Savings and Time Deposits.
Broad money supply (M-3)*	M-3 + Commercial Banks Foreign Currency Deposits (CBFCD)+ Non-Bank Financial Institutions (NBFI) Foreign Currency Deposits.

[14] Series were selected on the basis of data availability and prior knowledge of seasonal patterns affecting the series.
[15] The graphical inspection of the DPI and tests for seasonality showed that seasonality was insignificant. As a result this series was not seasonally adjusted.

i. Real Sector

The real economic time series for the period 2004 to 2010 are displayed graphically in Box 1 below.

Box 1
Selected Real Economic Time Series



Source: Central Statistical Office and Central Bank of Trinidad and Tobago.

The graphical representation of the QGDP Index, LSC, RSI and PMVS in Box 1 revealed clear seasonal patterns. This was confirmed by the plots of seasonal factors[16] (Box 2), which gives clearer depictions of seasonality in the time series. The QGDP Index, RSI and PMVS experience similar seasonal peaks during the fourth quarters (due to the Christmas related activity) and seasonal troughs in the first quarters as a result of low expenditure/demand following the Christmas season. LSC, which is highly correlated with construction activity, also showed the presence of marked stable seasonality. Specifically, cement sales tend to be higher in the first half of the year compared to the

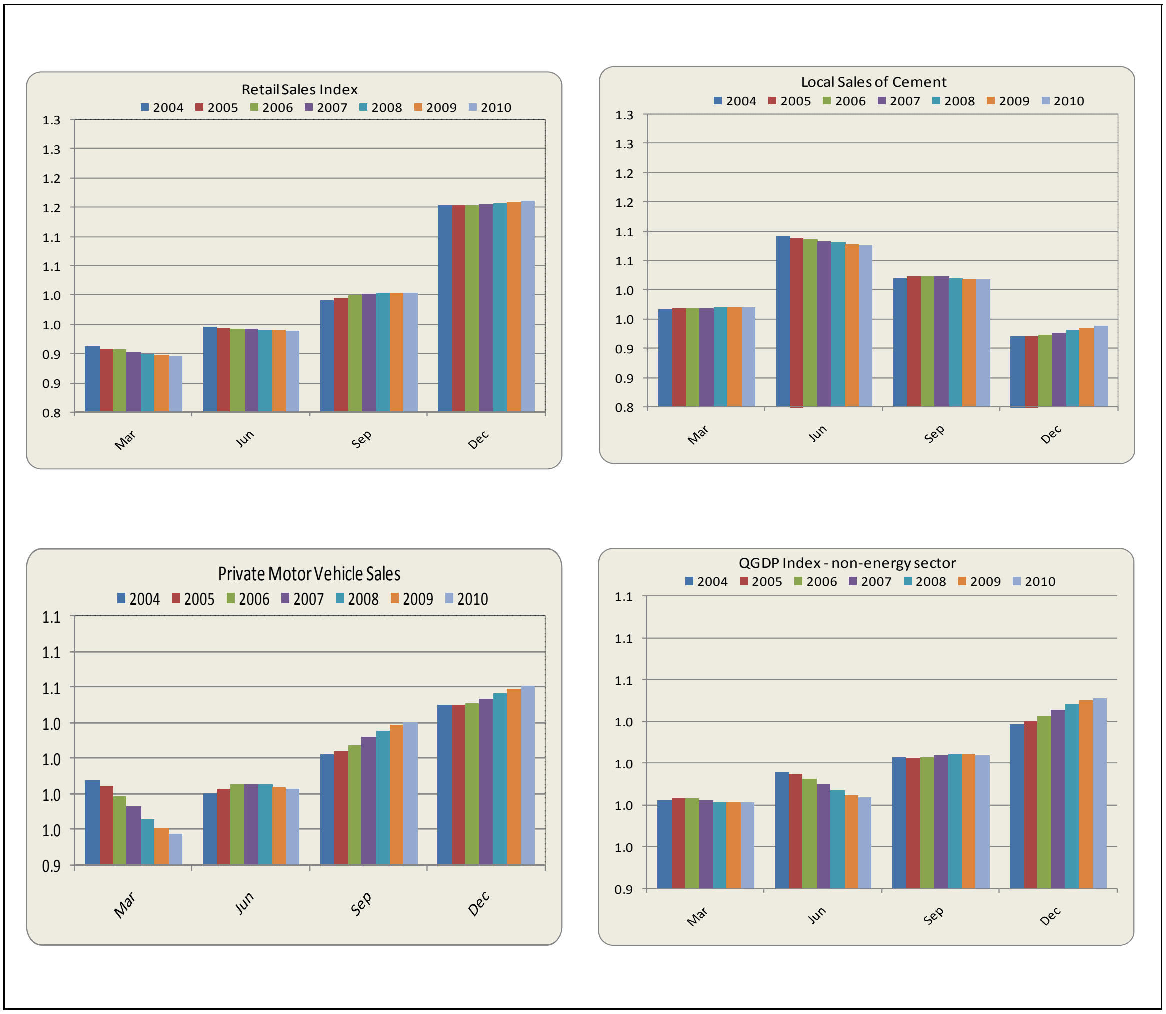
[16] The seasonal factors were derived from the X-12-ARIMA program subsequent to seasonal adjustment. Seasonal factors derived from the TRAMO/SEATS program also yielded analogous trends.

second half of the year when the rainy season sets in. Distinct seasonal troughs normally occur during the fourth quarter (i.e. the first quarter of the fiscal year which runs from October to December) while seasonal peaks arise in the second quarter (i.e. the third quarter in the fiscal year). In addition, LSC tend to be higher in the third quarter relative to the fourth quarter as construction activity picks-up during the Petite Careme period[17].

During the period 1994 to 2008, the Trinidad and Tobago economy experienced fifteen successive years of economic growth. Box 1 shows that the QGDP Index, LSC, RSI and PMVS displayed a rising trajectory during the period 2004 to 2008. However, the domestic economy experienced two consecutive years of decline in 2009 and 2010 as the global financial and economic crisis unfolded. As a result most real economic time series trended downward after 2009. The declining trend in local sales of cement varied directly with the construction sector. During the economic downturn, the levels of the series declined but the observed seasonal patterns remained relatively stable.

[17] A short period of dry weather in September.

Box 2
Seasonal Factors of Real Economic Time Series



Since the TRAMO/SEATS program contains no tests for seasonality, the F test and the Kruskal Wallis Chi Square tests provided by the X-12-ARIMA program (Table 4) were used to test for seasonality in the original time series.

Table 4
Tests for Seasonality in Real Economic Time Series

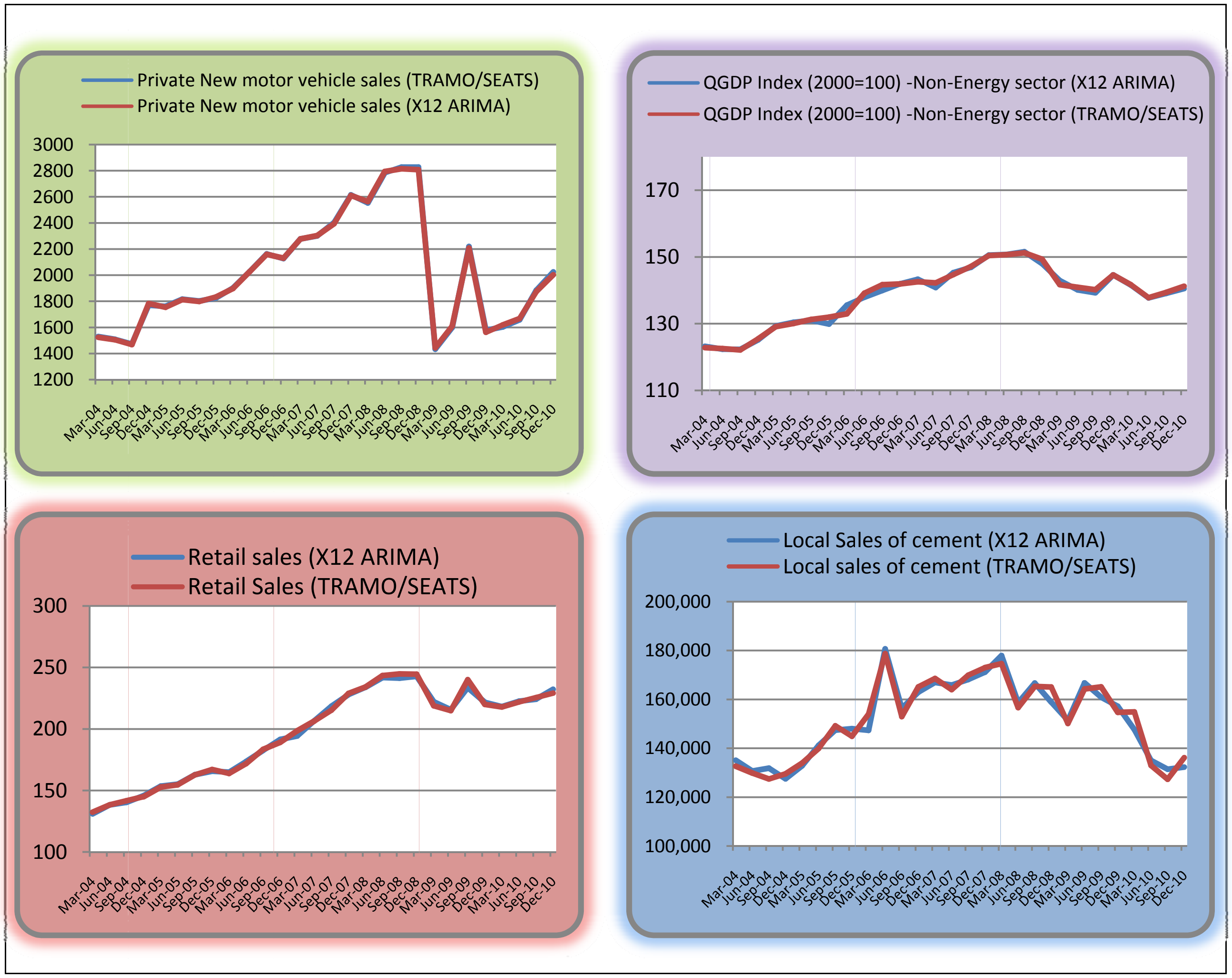
Test	*Statistic*	*P -value*	*0.1% level*	*1% level*	*5% level*	*Conclusion*[18]
RSI						
F test	159.1	0.00%	Significant	Significant	Significant	Seasonality present
Kruskal Wallis Chi square test	37.7	0.00%	Significant	Significant	Significant	Seasonality present
PMVS						
F test	33.6	0.00%	Significant	Significant	Significant	Seasonality present
Kruskal Wallis Chi square test	27.4	0.00%	Significant	Significant	Significant	Seasonality present
QGDP Index-Non-Energy Index						
F test	91.7	0.00%	Significant	Significant	Significant	Seasonality present
Kruskal Wallis Chi square test	38.0	0.00%	Significant	Significant	Significant	Seasonality present
Local Sales of Cement						
F test	88.7	0.00%	Significant	Significant	Significant	Significant
Kruskal Wallis Chi square test	36.2	0.00%	Significant	Significant	Significant	Significant

The combined statistical tests for "identifiable seasonality" confirm the informal observations. For all levels of significance, the conclusions of both the F tests and the Kruskal Wallis Chi square tests indicate the presence of seasonality in the QGDP Index, LSC, RSI and PMVS. However, at the disaggregated level, seasonality was not statistically significant in a few component series (sectors) of the QGDP Index, namely the manufacturing, government and finance sectors (Appendix 1, Table 1.2).

The RSI and QGDP Index were adjusted indirectly while PMVS and LSC were adjusted directly. The use of indirect adjustment was carried out on the aggregate series after visual inspection of the plots of the component series revealed varying seasonal patterns. For example, the sub-industries of the RSI showed distinct seasonal patterns. In particular, sales of dry goods, household appliances, furniture and other furnishings and supermarket and grocery products displayed clear seasonal patterns while retail sales of motor vehicles and parts showed no signs of seasonality. Several sectors within the non-energy sector (manufacturing, finance and government) displayed no seasonal patterns while other sectors (distribution, transport, construction, electricity and water and agriculture) exhibited clear signs of seasonal influences. In addition, correlation coefficients also suggest that the component series were not all strongly correlated. Indirect adjustment was also chosen in order to avoid statistical discrepancies via the loss of additivity. The seasonally adjusted series from both the X-12-ARIMA and the TRAMO/SEATS programs are displayed in Box 3 below.

[18] X-12-ARIMA program combines the F test for moving seasonality and the F test and Kruskal Wallis Chi Square test for seasonality to determine if "identifiable seasonality" is present in the series.

Box 3
Seasonally Adjusted Economic Time Series

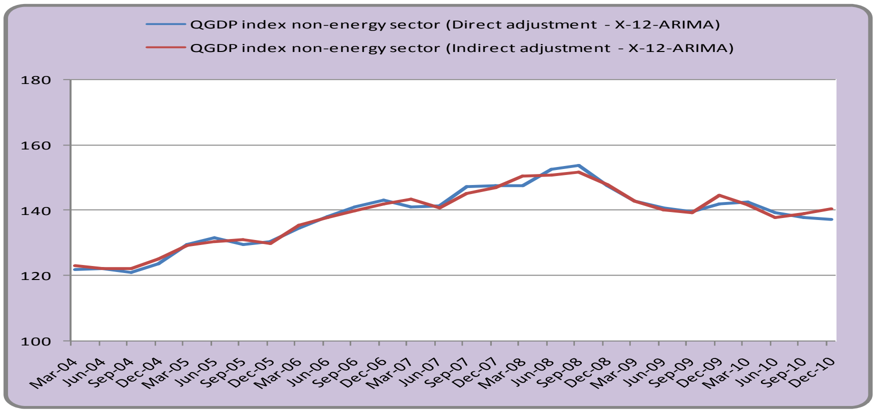


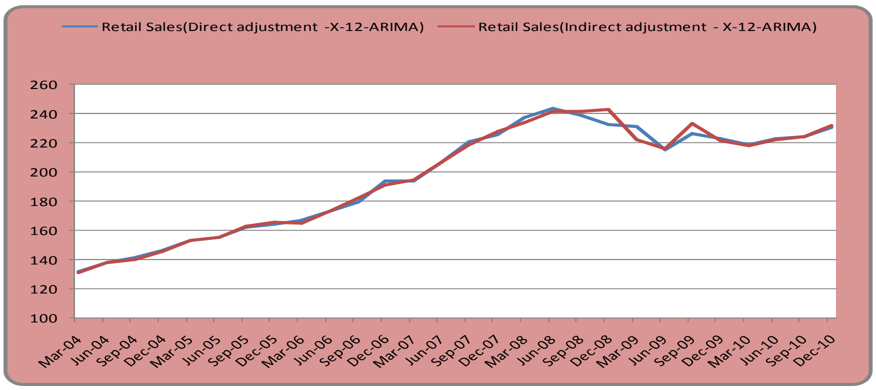
As Box 3 illustrates, the trends of the seasonally adjusted series derived from both programs are very comparable and almost identical in most cases.

At the disaggregate level, component series with no statistical evidence of seasonality (Appendix 1, Table 1.2) were not seasonally adjusted when the aggregate series were adjusted indirectly.

The seasonally adjusted estimates derived from indirect seasonal adjustment were also comparable to the estimates generated from direct seasonal adjustment. The graphical depiction of the direct and indirect seasonal adjusted aggregate series generated from the X-12-ARIMA program is presented in Box 4 below:

Box 4
Indirect and Direct Seasonally Adjusted Estimates of Aggregate Series.





Diagnostics

Residual Seasonality

For economic time series adjusted by the TRAMO/SEATS program, the combined Kruskal-Wallis Chi square statistic and the F tests from the X-12-ARIMA program indicate the absence of identifiable seasonality (i.e. the absence of residual seasonality). Seasonally adjusted series from the X-12-ARIMA program also contained no residual seasonality according to the conclusions of the F tests. The F tests results for residual seasonality are contained in Table 5 below.

Table 5
Testing For Residual Seasonality

F Test	*F Statistic*	*P -value*	*1% level*	*5% level*	*Conclusion*
X-12-ARIMA					
RSI	0.6	63.1%	Insignificant	Insignificant	Residual seasonality not present
PMVS	1.0	39.1%	Insignificant	Insignificant	Residual seasonality not present
Local Sales of Cement	0.4	73.3%	Insignificant	Insignificant	Residual seasonality not present
QGDP Index-Non-Energy Index	1.84	15.6%	Insignificant	Insignificant	Residual seasonality not present
TRAMO/SEATS					
RSI	1.7	18.9%	Insignificant	Insignificant	Residual seasonality not present
PMVS	1.8	15.7%	Insignificant	Insignificant	Residual seasonality not present
QGDP Index-Non-Energy Index	0.9	42.8%	Insignificant	Insignificant	Residual seasonality not present
Local Sales of Cement	0.43	73.3%	Insignificant	Insignificant	Residual seasonality not present

Residual seasonality was not statistically significant in any of the seasonally adjusted series derived from the X-12-ARIMA program. However, among the TRAMO/SEATS seasonally adjusted series, there was some evidence of residual seasonality in the seasonally adjusted series for local sales of cement at the 5 per cent level of significance.

At the disaggregated level, residual seasonality was not significant in any of the adjusted component series. Statistical tests (Kruskal Wallis Chi square and F tests) from the X-12-ARIMA program confirmed the absence of residual seasonality among the seasonally adjusted component series from both programs (Appendix 1, Table 1.2). Therefore, in the context of residual seasonality, both programs performed well.

Idempotency

Table 6 provides the idempotency values for the seasonally adjusted series from both programs.

Table 6
Idempotency Statistic Values

	Retail Sales Index	QGDP Index – non-energy sector	Private motor vehicle sales	Local Sales of Cement
X-12-ARIMA	0.00	0.00	0.00	0.00
TRAMO/SEATS	0.00	0.00	0.00	0.00

Table 6 indicates that idempotency values for series adjusted from both programs were equivalent to zero. Therefore, both programs performed well in the removal of seasonality from the original series.

Sliding Spans Analysis, History Diagnostics and Monitoring and Quality Assessment statistics

The seasonal adjustment of real economic time series by the X-12-ARIMA program passed both the sliding spans analysis and the monitoring and quality assessment statistics. The indirect seasonal adjustment of the RSI satisfied the monitoring and quality assessment statistics and yielded impressive sliding spans results which showed that none of the seasonal factors (0 per cent of the seasonal factors) and quarter-on-quarter changes were unstable. Among the component series (sub-industries) of the RSI, only sales of household appliances, furniture and furnishings had unstable seasonal factors outside the recommended range. However this series was still seasonally adjusted since the percentage of unstable seasonal factors was just outside the recommended range.

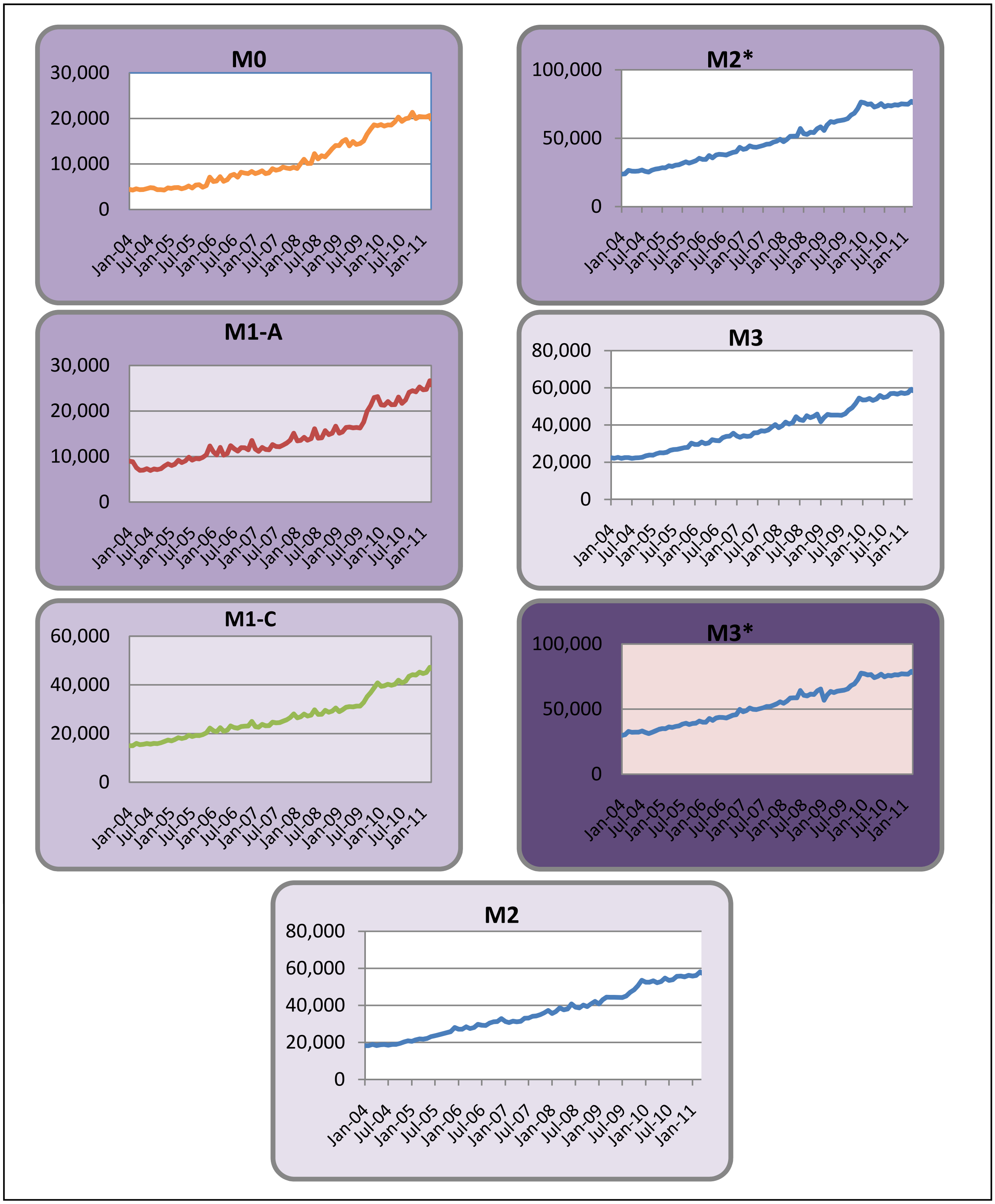
Similarly, the QGDP Index passed both sets of tests. At the sectoral level, only the agriculture sector index failed both the sliding spans analysis and the monitoring and quality assessment statistics. The sliding spans results showed that a significant percentage (over 50 per cent) of seasonal factors were unstable. This result is attributable to the significant fluctuations in the production of agricultural products. The substantial wavering nature of agriculture production was also evident from the results of the monitoring and quality assessment statistics. The seasonal adjustment estimates failed the M8, M9, M10 and M11 statistics. This indicates that the series is characterized by large fluctuations in the seasonal component which leads to unreliable seasonally adjusted estimates. As a result, the agriculture index was not seasonally adjusted. The seasonal adjustment of PMVS and LSC also passed both sets of diagnostics (Appendix 1, Table 1.3).

The history analysis from the first quarter of 2008 was also examined for the aggregate series. Results showed that the use of indirect seasonal adjustment (for the QGDP Index) performed marginally better than direct seasonal adjustment as indirect adjustment recorded a smaller value of the “average absolute revision” statistic provided by the X-12-ARIMA program (Appendix 1, Table 1.4).

ii. Monetary Aggregates

The monetary aggregate series for the period January 2004 to April 2011 are presented graphically in Box 5 below.

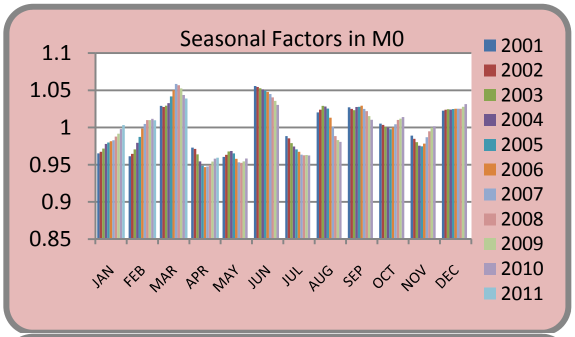
Box 5
Monetary Aggregates

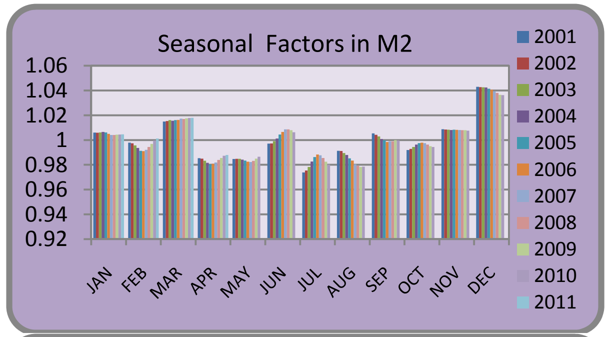


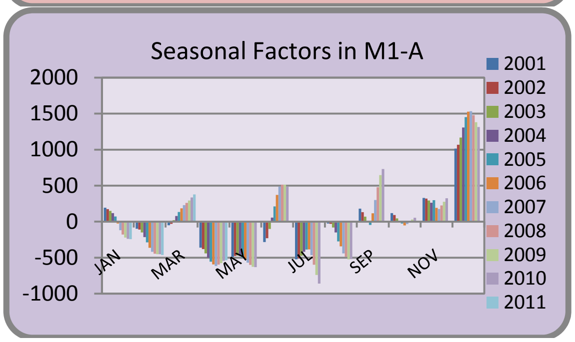
While the inherent seasonal patterns in monetary aggregates are unclear from the graphical depiction (Box 5), an evaluation of the seasonal factors[19] of the monetary aggregates and their components shown in Box 6 and Box 7, respectively, indicate the presence of seasonality in the monetary aggregates.

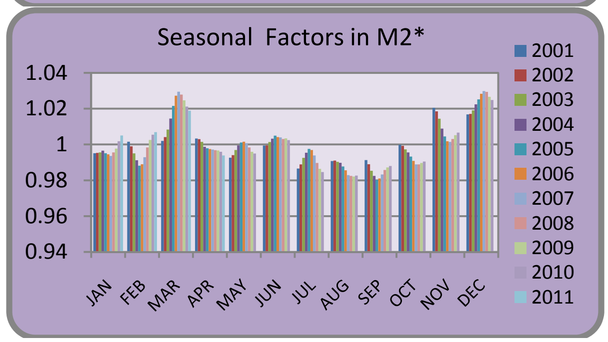
[19] The seasonal factors were derived from the X-12-ARIMA program subsequent to seasonal adjustment.

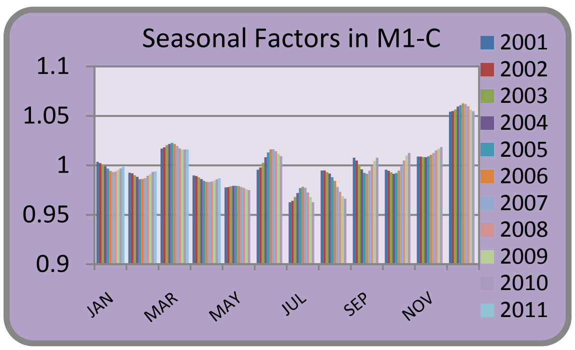
Box 6
Seasonal Factors of Monetary Aggregates

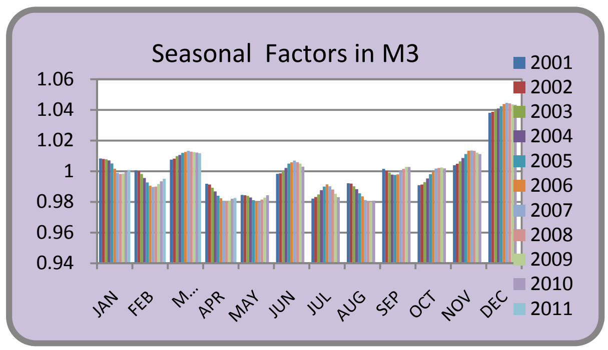


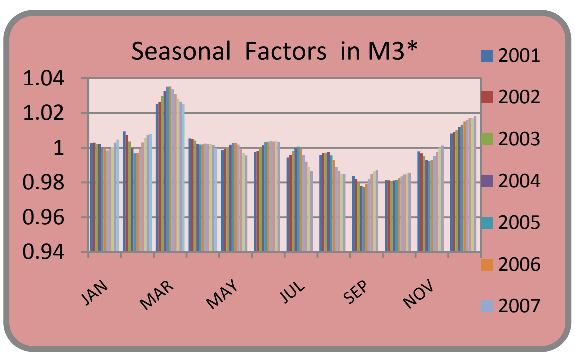




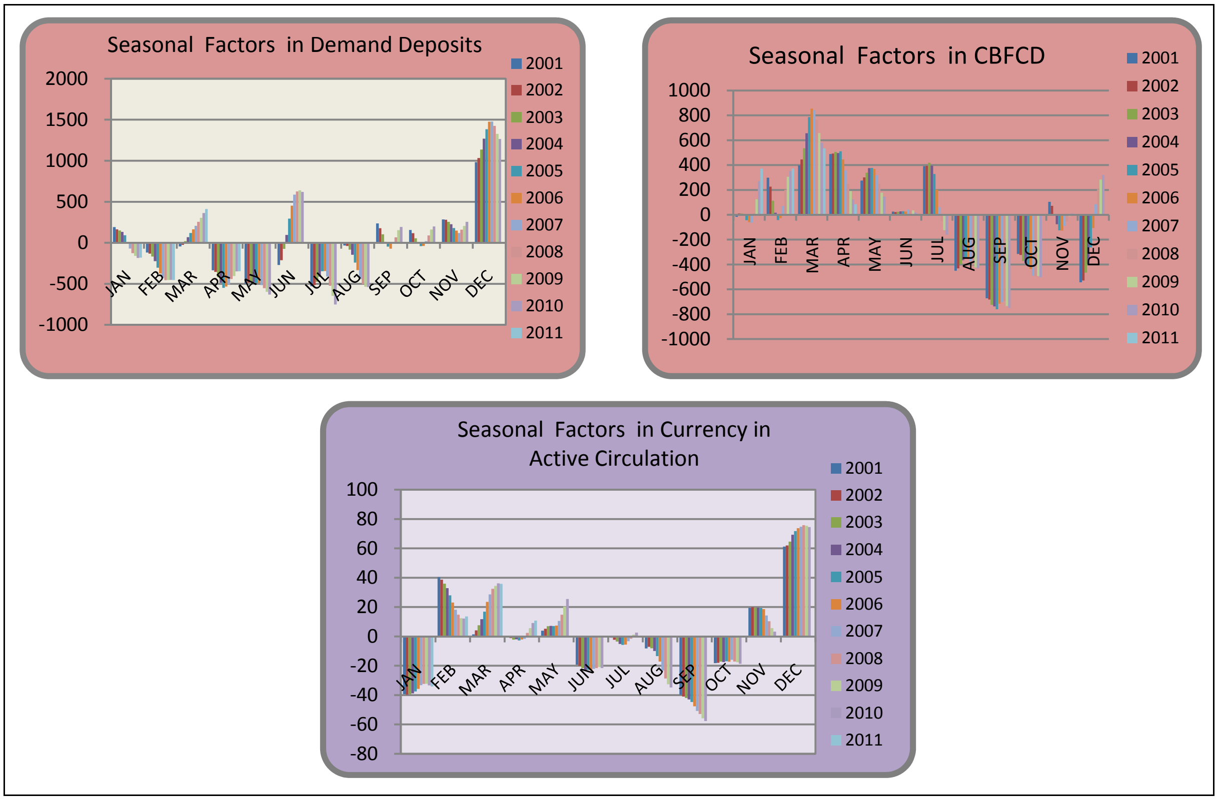








Box 7
Seasonal Factors[20] of Component Series



Box 6 illustrates clear seasonal patterns among the monetary aggregates which clearly mirror the seasonal factors among the component series (Box 7). For example, the M1 aggregate series tends to reflect the seasonal highs and lows in their component series, CAC and DD. Among the component series, there were clear signs of seasonality in CAC, CBFCD and DD. While Box 7 clearly shows varying seasonal patterns among the component series, seasonal peaks can be observed in December for CAC and DD.

The CAC series exhibits seasonal peaks in December due to increased cash transactions during the Christmas period. Businesses also tend to demand more credit during this period as they attempt to take advantage of increased sales. Subsequently, seasonal lows in January reflect reductions in consumer spending following the Christmas season. In addition, the series demonstrates moderate seasonal highs in February and March due to the carnival celebrations in Trinidad & Tobago.

DD exhibits seasonal peaks in December, with moderate seasonal highs observed at the end of each quarter. This may be related to the payment of corporation taxes due at the end of each quarter. In preparation for tax payments, corporations may transfer some of their funds from short term non liquid instruments such as treasury bills to liquid

[20] Only seasonal factors of series with statistically significant seasonality are included in Box 8.

investment instruments such as DD in order to facilitate the payments of corporate taxes. On the other hand, DD displays seasonal troughs in the months of February, April, May, July and August. The dips in July and August may be associated with "back to school" expenditure.

The CBFCD series displays seasonal peaks in March, February and April which may be related to increased tourist arrivals for the Carnival and Easter periods. The series also show seasonal troughs during the months of August, September, October and November which may be related to increased imports as companies accumulate stocks in anticipation of greater sales during the Christmas period.

However, no regular seasonal patterns were observed in the SD, TD, CBD, NBFI Foreign Currency Deposits and NBFI Saving and Time Deposits series.

Formal Testing For Seasonality

Table 7 illustrates the results of the formal tests for seasonality in the monetary aggregates.

Table 7
Tests for Seasonality in Monetary Aggregates

Test	*Statistic*	*P -value*	*0.1% level*	*1% level*	*5% level*	*Conclusion*
M0 F test Kruskal Wallis Chi square test	4.491 43.69	0.00% 0.00%	Significant Significant	Significant Significant	Significant Significant	Identifiable Seasonality Present
M1-A F test Kruskal Wallis Chi square test	10.554 66.2097	0.00% 0.00%	Significant Significant	Significant Significant	Significant Significant	Identifiable Seasonality present
M1-C F test Kruskal Wallis Chi square test	23.989 80.4739	0.00% 0.00%	Significant Significant	Significant Significant	Significant Significant	Identifiable Seasonality present
M2 F test Kruskal Wallis Chi square test	21.987 76.34	0.00% 0.01%	Significant Significant	Significant Significant	Significant Significant	Identifiable Seasonality present
M2* F test Kruskal Wallis Chi square test	3.381 40.032	0.00% 0.00%	Significant Significant	Significant Significant	Significant Significant	Identifiable Seasonality Present
M3 F test Kruskal Wallis Chi square test	15.325 69.69	0.00% 0.00%	Significant Significant	Significant Significant	Significant Significant	Identifiable Seasonality present
M3* F test Kruskal Wallis Chi square test	7.773 56.30	0.00% 0.00%	Significant Significant	Significant Significant	Significant Significant	Identifiable Seasonality present

The conclusions of the combined statistical tests for “identifiable seasonality” indicate that seasonality was significant in all of the monetary aggregates at the conventional levels of significance. This is attribuatble to significant seasonality in the CAC, DD and CBFCD components (Appendix 1, Table 1.5). On the other hand seasonality was not statistically significant in the remaining component series (SD, TD, NBFI Foreign Currency Deposits, CBD and NBFI Savings and Time Deposits series). Intuitively, SD and TD are regarded as long term investment instruments and are not likely to contain seasonality.

As a result, seasonality was more evident among the monetary aggregates whose components contained strong seasonality. For example, seasonality was particularly strong in the M1-A and M1-C series due to presence of seasonality in their dominant components; CAC and DD, while seasonality was not strong in the M0 series due to the absence of seasonality in the CBD.

Monetary aggregates were seasonally adjusted using the indirect method in order to maintain additivity and avoid statistical discrepancies. Evidence of varying seasonal patterns among the component series also supports the use of the indirect seasonal adjustment. For example, within the M1-C series, CAC and DD have clear seasonal patterns while the SD series displays no signs of seasonality. Seasonal adjustment of monetary aggregates was performed using both the X-12-ARIMA and the TRAMO/SEATS programs. Seasonally adjusted series derived from both programs for the period 2006 to 2011 are contained in Box 8.

Box 8
Seasonally Adjusted Monetary Aggregates

Box 8 confirms that the trends of the seasonally adjusted monetary aggregates from both programs were comparable.

On the other hand, evidence suggests that the direct seasonal adjustment method was also suitable for some of the monetary aggregates. For instance, some of the component series (e.g. DD and CAC) produced high correlation coefficients. Nevertheless, the seasonally adjusted estimates derived from the indirect method also performed well when compared to the estimates derived from the direct method (Appendix 2, Box 2.2).

Further Tests for Residual Seasonality

Table 8 outlines the results of the F tests for residual seasonality.

Table 8
Tests for Residual Seasonality in Monetary Aggregates

F Test	*F Statistic*	*P -value*	*0.1% level*	*1% level*	*5% level*	*Conclusion*
X-12-ARIMA						
M0	0.83	62.6	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M1-A	0.72	71.7%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M1-C	0.62	80.6%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M2	0.53	87.9%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M2*	0.09	100.09%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M3	0.46	92.4%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M3*	0.12	100.07%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
TRAMO/SEATS						
M0	4.098	0.00%	Significant	Significant	Significant	Residual Seasonality present
M1-A	0.817	62.30%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M1-C	0.796	64.32%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M2	0.842	59.84%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M2*	3.178	0.09%	Significant	Significant	Significant	Residual Seasonality Present
M3	1.032	42.36%	Insignificant	Insignificant	Insignificant	Residual Seasonality not Present
M3*	2.669	0.44%	Insignificant	Significant	Significant	Residual Seasonality not Present at 0.1% level.

The F tests results contained in Table 8 show that the seasonally adjusted series from the X-12-ARIMA program contained no residual seasonality. In contrast, there was evidence of residual seasonality in some of the seasonally adjusted monetary aggregates from the TRAMO/SEATS program; M0 and M2* (at all conventional levels of significance) and M3* (at levels of significance higher than 0.1 per cent).

At the component level, the conclusions of the F tests indicate the absence of residual seasonality among the seasonal adjusted component series from both the X-12-ARIMA and TRAMO/SEATS programs (Appendix 1, Table 1.5)

Sliding Spans Analysis, History Diagnostics and Monitoring and Quality Assessment statistics

With the exception of the M0 series, all seasonally adjusted aggregate series from the X-12-ARIMA program passed the monitoring and quality assessment statistics (Appendix 1, Table 1.6). The M0 series marginally failed the M7, M8, M10 and M11 statistics which suggests the amount of moving seasonality relative to stable seasonality is high and significant fluctuations in the seasonal component. These lead to unreliable seasonally adjusted estimates. This occurred as one of its component series, the CBD, failed the M7, M8 and M10 statistics. Nevertheless, the M0 series was seasonally adjusted given its marginal failure of these diagnostics. At the component level, DD, CAC and CBFCD passed the Monitoring and Quality Assessment statistics.

Sliding spans analysis was not produced for most of the monetary aggregates which limits the discussion on the stability of the seasonally adjusted estimates. Sliding spans analysis is normally not provided for series that are decomposed additively (e.g. M1-A) and where the range of seasonal factors are too low (e.g. M2*, M3 and M3*). Sliding spans analysis was provided only for the M1-C and M2 aggregates which showed the absence of insignificant percentages of unstable seasonal factors. At the component level, DD, CAC and CBFCD were decomposed additively and sliding spans analysis was not produced.

Examination of the revision history analysis provided by the X-12-ARIMA program indicates that the use of the indirect seasonal adjustment method performed better in the context of achieving smaller average revisions with the availability of new data. The “average absolute revision” values for the indirect seasonal adjustment method were generally smaller when compared to the direct method (Appendix 1, Table 1.4)

4. Conclusion

This study examined the performances of two seasonal adjustment programs, X-12-ARIMA and TRAMO/SEATS on selected economic time series in Trinidad and Tobago. Results indicate that seasonality was significant in the real economic time series and monetary aggregates. This suggests that formal seasonal adjustment should be conducted on a more regular basis. This would assist analysts in more clearly understanding the underlying trends and patterns in high frequency data as well as in forecasting intra-year patterns more precisely. Given the presence of significant seasonality in the monetary data, it is suggested that seasonally adjusted series be published for both monetary aggregates and their components (e.g. M1-A, M1-C, CAC, DD, CBFCD, Etc.) alongside the raw data and all related metadata (e.g. software used, the criteria for choosing seasonal adjustment option, the aggregation policy and a clear revision policy). The seasonally adjusted QGDP index should also be retained and the seasonal patterns updated as necessary.

Finally, this paper recommends that the X-12-ARIMA program be adopted for seasonal adjustment. In the context of the performance of both programs, the X-12-ARIMA program performed better in the achievement of residual seasonality since a couple of adjusted monetary aggregates from the TRAMO/SEATS program contained residual seasonality. The X-12-ARIMA program also provides a wide range of diagnostics to test the quality of the seasonal adjustment method.

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Appendix 1
Supplementary Tables

Table 1.1

MONITORING AND QUALITY ASSESSMENT STATISTICS	
1. The relative contribution of the irregular over one quarter span.	M1
2. The relative contribution of the irregular component to the stationary portion of the variance.	M2
3. The amount of quarter to quarter change in the irregular component as compared to the amount of quarter to quarter change in the trend-cycle.	M3
4. The amount of autocorrelation in the irregular as described by the average duration of run.	M4
5. The number of quarters it takes the change in the trend-cycle to surpass the amount of change in the irregular.	M5
6. The amount of year to year change in the irregular as compared to the amount of year to year change in the seasonal.	M6
7. The amount of moving seasonality present relative to the amount of stable seasonality.	M7
8. The size of the fluctuations in the seasonal component throughout the whole series.	M8
9. The average linear movement in the seasonal component throughout the whole series.	M9
10. Same as 8, calculated for recent years only.	M10
11. Same as 9, calculated for recent years only.	M11

Notes:

1. All the measures below are in the range from 0 to 3 with an acceptance region from 0 to 1.
2. M7 is the most important among the M-diagnostics. An M7 value greater than one indicates that moving seasonality is large relative to the amount of stable seasonality which leads to unreliable estimates of seasonal factors.
3. An M1 value greater than 1 indicates that the irregular component is too large for the accurate estimation of the seasonal component.
4. The M8, M9, M10, and M11 diagnostics show the fluctuations in the seasonal component. These diagnostics show potential problems in the seasonal component (e.g. seasonal breaks) which leads to unreliable estimates of the seasonal components.

Table 1.2
Seasonality and Residual Seasonality Tests (Real Economic Time Series)

Component series	Seasonality	Residual Seasonality (1)[21]	Residual Seasonality(2)[22]
QGDP Index-Non-Energy sector			
Agriculture	Significant	Insignificant	Insignificant
Manufacturing	Insignificant	Insignificant	Insignificant
Electricity and Water	Seasonality Present	Insignificant	Insignificant
Construction	Significant	Insignificant	Insignificant
Distribution	Significant	Insignificant	Insignificant
Transport	Significant	Insignificant	Insignificant
Government	Insignificant	Insignificant	Insignificant
Finance	Insignificant	Insignificant	Insignificant
Other services	Insignificant	Insignificant	Insignificant
Retail Sales Index			
Dry Goods	Significant	Insignificant	Insignificant
Hardware and Construction materials	Significant	Insignificant	Insignificant
Supermarket and Groceries	Significant	Insignificant	Insignificant
Appliances, Furniture and other Furnishings	Significant	Insignificant	Insignificant
Motor Vehicles and Parts	Insignificant	Insignificant	Insignificant
Textiles and Wearing Apparels	Significant	Insignificant	Insignificant
Petrol Filling Stations	Significant	Insignificant	Insignificant
Other	Significant	Insignificant	Insignificant

[21] Conclusions of residual seasonality test on seasonally adjusted series from the X-12-ARIMA program.
[22] Conclusions of residual seasonality test on seasonally adjusted series from the TRAMO/SEATS program.

Table 1.3
Sliding Spans and Monitoring and Quality Assessment Statistics (Real Economic Time Series)

Series	Sliding Spans	Monitoring and Quality Assessment Statistics
QGDP Index-Non-Energy sector	Insignificant percentage of unstable seasonal factors.	Accepted
Agriculture	Significant percentage of unstable seasonal factors.	Accepted
Manufacturing[23]	-	-
Electricity and Water	Insignificant percentage of unstable seasonal factors.	Accepted
Construction	Insignificant percentage of unstable seasonal factors.	Accepted
Distribution	Insignificant percentage of unstable seasonal factors.	Accepted
Transport	Insignificant percentage of unstable seasonal factors.	Rejected
Government	-	-
Finance	-	-
Other services	-	-
Retail Sales Index	Insignificant percentage of unstable seasonal factors.	Accepted
Dry Goods	Insignificant percentage of unstable seasonal factors.	Accepted
Hardware and Construction materials	Insignificant percentage of unstable seasonal factors.	Accepted
Supermarket and Groceries	Insignificant percentage of unstable seasonal factors.	Accepted
Appliances, Furniture and other Furnishings	Insignificant percentage of unstable seasonal factors.	Accepted
Motor Vehicles and Parts	-	-
Textiles and Wearing Apparels	Insignificant percentage of unstable seasonal factors.	Accepted
Petrol Filling Stations	Insignificant percentage of unstable seasonal factors.	Accepted
Other	Insignificant percentage of unstable seasonal factors.	Accepted
Local Sales of Cement	Insignificant percentage of unstable seasonal factors.	Accepted
Private motor vehicle sales	Insignificant percentage of unstable seasonal factors.	Accepted

[23] The Manufacturing sector was decomposed additively. The sliding spans do not work for an additive decomposition.

Table 1.4
Revisions History Analysis

Aggregates series	Average absolute percent revisions –Direct Seasonal Adjustment	Average absolute percent revisions –Indirect Method of Seasonal Adjustment	Method preferred
Real sector aggregates			
RSI	0.42	0.89	Direct seasonal Adjustment
QGDP	0.53	0.23	Indirect Seasonal adjustment
Monthly Monetary Aggregates			
M0	0.99	0.07	Indirect Seasonal adjustment
M1-A	0.82	0.66	Indirect Seasonal adjustment
M1-C	0.64	0.34	Indirect Seasonal adjustment
M2	0.47	0.25	Indirect Seasonal adjustment
M2*	0.45	0.39	Indirect Seasonal adjustment
M3	0.41	0.24	Indirect Seasonal adjustment
M3*	0.47	0.36	Indirect Seasonal adjustment

Table 1.5

Seasonality and Residual Seasonality Tests (Monetary Component Series)

Component series	Seasonality	Residual Seasonality (1)[24]	Residual Seasonality(2)[25]
Currency in Active Circulation	Significant	Insignificant	Insignificant
Demand Deposits	Significant	Insignificant	Insignificant
Time Deposits	Insignificant	Insignificant	Insignificant
Saving Deposits	Insignificant	Insignificant	Insignificant
Commercial Banks Foreign Currency Deposits	Significant	Insignificant	Insignificant
Commercial Banks' Deposits at Central Bank	Insignificant	Insignificant	Insignificant
Non Financial Institutions Savings and Time Deposits	Insignificant	Insignificant	Insignificant
Non Financial Institutions Foreign Currency Deposits	Insignificant	Insignificant	Insignificant

[24] Conclusion of residual seasonality test on series adjusted in the X-12-ARIMA program.
[25] Conclusion of residual seasonality test on series adjusted in the TRAMO/SEATS program.

Table 1.6

Sliding Spans and Monitoring and Quality Assessment Statistics: Monetary Aggregates

Series	Sliding Spans	Monitoring and Quality Assessment Statistics
M0	-	Conditionally Rejected
M1-A	-	Accepted
M1-C	Insignificant percentage of unstable seasonal factors.	Accepted
M2	Insignificant percentage of unstable seasonal factors.	Accepted
M2*	-	Accepted
M3	-	Accepted
M3*	-	Accepted

Appendix 2

Box 2.1

The US Census Bureau X-12-ARIMA Program - Method of Seasonal Decomposition

X-12-ARIMA program performs an AIC (Akaike Information Criterion) based selection to decide between a log transformation (multiplicative model) and no transformation (additive model) of the input series. To decide which transformation to use, and therefore the decomposition model, the X-12-ARIMA program fits a regARIMA model to the untransformed and transformed series and the selection criteria is based on AICC comparisons.

Log transformation is used except when:

$AICC_{nolog} – AICC_{log} < \Delta_{AICC}$

Where:

$AICC_{nolog}$ = AICC value from fitting the regARIMA model to the untransformed series.

$AICC_{log}$ = AICC value from fitting the regARIMA model to the transformed series.

Δ_{AICC} = value entered for the aicdiff argument, with a default of -2.

1. The program fits a regression-ARIMA model to the input series (depending on the transformation chosen from the above criteria) in order to:
   - Detect and adjust for outliers and other distorting effects.
   - Improve forecasts and seasonal adjustments.
   - Detect and estimate additional components such as calendar effects.
   - Extrapolate forecasts and backcasts for an extra one to three years of data.

2. Using the pre-adjusted time series, the X-12-ARIMA process makes a rough estimate of the trend-cycle component using a 2x4 term moving average. This first estimate of trend-cycle component is very smooth and will tend to obscure some of the detail of its movements, but as the algorithm proceeds, progressively better estimates will be obtained.

3. Having obtained the trend-cycle component, the combined seasonal and irregular components are then derived by dividing the pre adjusted series by the first estimate of the trend-cycle component in the case of a multiplicative model (but subtracted in the case of an additive model). Four time series are then formed from the aggregated seasonal-irregular time series; time series of first quarters, second quarters, third quarters and fourth quarters' estimates. A moving average is then carried out on each of the four series to smooth out the irregular component and give an estimate of the seasonal component for each quarter. The first estimate of the seasonal adjusted series is derived by dividing the pre-adjusted series by the estimate of the seasonal component.

4. A second round of iteration is performed having derived the first estimate. A new estimate of the trend-cycle component is computed by applying a type of moving average - the Henderson moving average. The Henderson moving average, which produces more accurate estimates of the trend-cycle component when compared to the 2x4-term moving average, can only be used on series which do not exhibit seasonality. The previous two steps are repeated twice. On each occasion, the Henderson moving average is applied to the latest estimate of the seasonally adjusted series to obtain an estimate of the trend-cycle component. At each stage, increasingly better estimates of each of the components are obtained until at the end of the third iteration when the final estimate of the seasonal component of the pre-adjusted series is produced.

5. Finally, the best estimate of the seasonally adjusted series is found by dividing the original series by the latest estimated seasonal component of the pre-adjusted series.

Box 2.2

Direct and Indirect Seasonal Adjustment of Monetary Aggrgates