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From noise to turning points: A new framework for seasonal adjustment in Armenia

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FROM NOISE TO TURNING POINTS

A NEW FRAMEWORK FOR SEASONAL ADJUSTMENT IN ARMENIA

Gevorg Minasyan, Stefan Schipper, Lusya Khachatryan, Seda Movsisyan, and Pamela Lapitan

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ABSTRACT

This paper evaluates the transition from X12-ARIMA to X13-ARIMA-SEATS for the seasonal adjustment of Armenia's quarterly national accounts (QNA). We analyze the methodological advancements and their impact on key economic indicators, focusing on the precision and reliability of seasonally adjusted data. Our findings suggest that the indirect seasonal adjustment method, despite larger revisions, is preferable, given potential variations in seasonal patterns among gross domestic product components and strong user preferences for preserving accounting relationships. Furthermore, a partial concurrent update strategy achieves a better balance between accuracy and revision minimization compared to current or fully concurrent methods. Finally, deriving seasonally adjusted price deflators from seasonally adjusted volume and current price data aligns more closely with the underlying economic structure of Armenian QNA, given that QNA data is available primarily in nominal terms. These results remain consistent across various sensitivity checks, supporting our methodological approach for analyzing Armenia's QNA series.

Keywords: Armenia, JDemetra+, national accounts, seasonal adjustment, X13-ARIMA-SEATS

JEL codes: C22, C32, C5

1. INTRODUCTION

Economic variables exhibit systematic and recurring within-year patterns influenced by a variety of factors, such as weather, institutions, and social customs and traditions. When these seasonal variations dominate changes in the original series from one period to another, identifying nonseasonal effects, including long-term movements, cyclical variations, and irregular factors—informative economic signals—becomes challenging. Timely identification of turning points in key macroeconomic variables, like the quarterly national accounts (QNA), requires the removal of seasonal and calendar effects from time series data. This process involves utilizing analytical techniques to break down the series into unobserved components, based on *a priori* assumptions regarding their expected behavior.

Removing the repeated impact of seasonal effects is important for both historical business cycle analysis and assessing current economic conditions. This helps in identifying fundamental long-run movements and short-run fluctuations in the time series, thereby enhancing the interpretation of economic variables and contributing to informed decision making. However, the challenge of precisely defining seasonality means that the different approaches may result in different outcomes. Analyst expertise remains essential for finetuning the seasonal adjustment procedures and verifying the accuracy of the adjusted statistics. Expert-driven judgment is particularly important in the current economic landscape, where linear filters are typically applied for seasonal component extraction despite the prevalence of uncertainties and nonlinear trends in many economic series.

The Statistical Committee of the Republic of Armenia (ARMSTAT) initiated its first seasonal adjustment of QNA in 1998, using the autoregressive integrated moving average (ARIMA) X11 method developed by the United States Census Bureau. In 2013, ARMSTAT shifted to the X12-ARIMA method and the Demetra+ program,¹ aligning with recommendations from the International Monetary Fund (IMF) and the United Nations Economic Commission for Europe. However, X12-ARIMA, while representing an advance on earlier methods, relies heavily on linear models, limiting its ability to capture the nonlinear trends increasingly present in modern economies. Recognizing this limitation, ARMSTAT transitioned to the X13-ARIMA-SEATS method and the JDemetra+ software in 2022, aligning with the European Statistical System (ESS) 2015 guidelines on seasonal adjustment and the IMF's QNA 2017 manual.

X13-ARIMA-SEATS offers several advantages over its predecessors. First, it incorporates the SEATS (signal extraction in ARIMA time series) method, specifically designed to handle nonlinear trends and structural breaks in time series data. Second, X13-ARIMA-SEATS provides a more advanced toolkit for diagnosing the quality and stability of seasonal adjustment models. Third, X13-ARIMA-SEATS can efficiently process multiple series simultaneously. In addition, JDemetra+ includes a more versatile interface compared to Demetra+, enabling users to apply tools such as nowcasting, temporal disaggregation, and benchmarking. Importantly, JDemetra+ provides common analysis options for different seasonal adjustment methods, allowing for easy comparison of results across these algorithms.

¹ ARIMA is a statistical method for analyzing and forecasting time series data by modeling its temporal structure, and Demetra+ is free software developed by the National Bank of Belgium for seasonal adjustment using TRAMO/SEATS and X12-ARIMA methods.

In this paper, we examine the implications of transitioning from the X12-ARIMA to the X13-ARIMA-SEATS method for the seasonal adjustment of Armenia's QNA series. Our analysis focuses on assessing the methodological advancements and their impact on the interpretation of key economic indicators, with a particular emphasis on the precision and reliability of seasonally adjusted data in capturing underlying economic trends. Additionally, we conduct a wide range of advanced quality diagnostics to validate the underlying assumptions of the new seasonal adjustment framework and the major decisions regarding various aspects of the methodology.

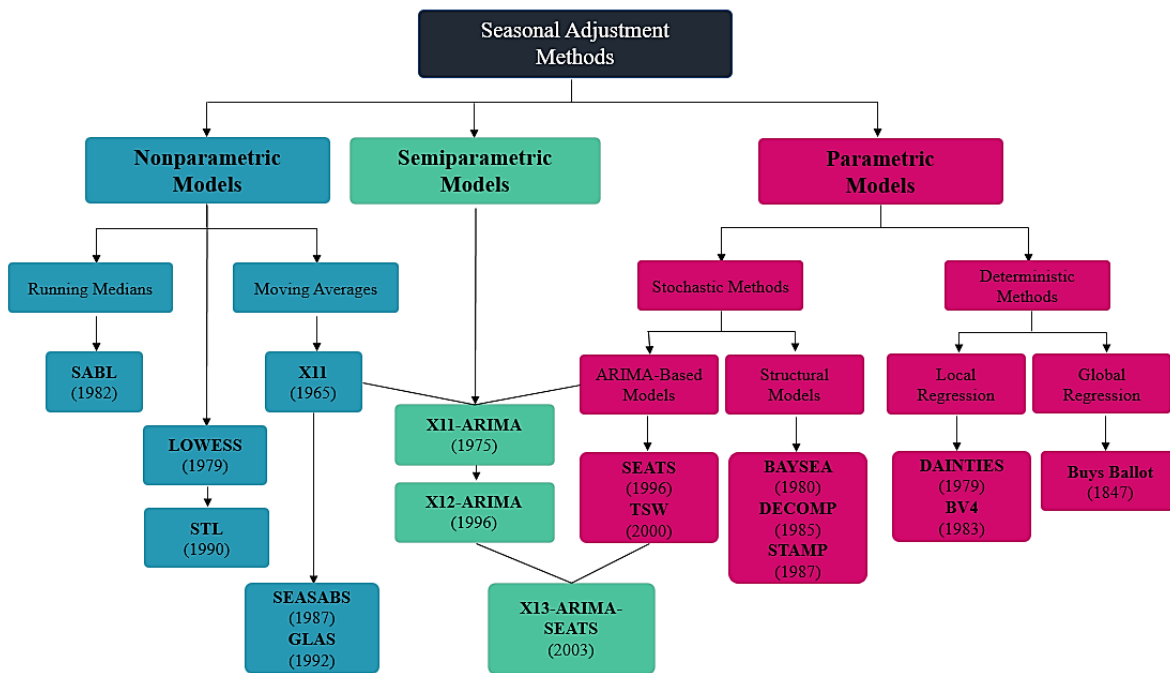
Our findings suggest that the new framework yields significant insights, particularly in the context of direct versus indirect adjustments, update strategies, and the relationship between price, volume, and value indices. While both direct and indirect approaches produce similar trends, notable discrepancies emerge, especially during crisis periods. The indirect method, despite its susceptibility to larger revisions, appears preferable, given the potential for divergent seasonal patterns among gross domestic product (GDP) components and user demand. Additionally, our exploration of update strategies highlights the advantages of a partial concurrent adjustment method, which balances accuracy with the minimization of revisions. Finally, the findings on the relationship between seasonally adjusted price, volume, and value indices indicate that deriving residuals from seasonally adjusted volume and current price data, rather than directly adjusting price deflators, aligns better with the underlying economic structure of the Armenian QNA. These results remain robust across various sensitivity checks, reaffirming the validity of our methodological approach and its applicability to the analysis of the Armenian QNA series.

The remainder of this paper is structured as follows: Section 2 reviews the literature on seasonal adjustment methods, Section 3 details the methodology employed, Section 4 presents findings, Section 5 discusses quality diagnostics, Section 6 addresses the pre-adjustment of QNA during the coronavirus disease (COVID-19) crisis, and Section 7 concludes with a summary.

2. LITERATURE REVIEW

Seasonal adjustment methods fall into three broad categories: (i) nonparametric methods, which rely on linear smoothing filters to adjust the data; (ii) parametric methods, where seasonal adjustment is achieved through explicit specification and estimation of unobserved components within the data; and (iii) and semiparametric methods, which combine aspects of both explicit and implicit modeling of each component (see Figure 1).

Figure 1: Classification of Seasonal Adjustment Methods



Source: Eurostat (2018).

2.1. Nonparametric Models

The most common seasonal adjustment methods use moving averages or linear smoothing filters to adjust data sequentially by adding and subtracting individual observations. A pioneer in this field was the United States Census Bureau's X11 program, released in 1965 (Shiskin, Young, and Musgrave 1967). This was the result of over a decade of development, beginning with Method I in 1954 and followed by 12 experimental variants of Method II (X0, X1, etc.), culminating in the release of X11 (Shiskin 1978).

Building on the foundation of X11, the Australian Bureau of Statistics introduced SEASABS (Seasonal Analysis at the Australian Bureau of Statistics) in 1987 (Eurostat 2018). This knowledge-based algorithm retains records of previous series analyses, enabling comparisons of X11 diagnostics and insights into the parameters that produced acceptable adjustments. Young (1992) developed another version, GLAS (General Linear Abstraction of Seasonality), at the Bank of England for seasonally adjusting monetary variables. This method estimates and smooths trend and seasonal components with a triangular-shaped weighting pattern in a moving average of data, and it incorporates Lane's (1972) minimum revision algorithm. Other similar tools include SABL (Seasonal Adjustment-Bell Laboratories) (Cleveland, Dunn, and Terpenning 1978), a robust alternative to X11 that tackles outliers and smooths trends without rigid data assumptions. STL (seasonal and trend decomposition using Loess), developed by Cleveland et al. (1990), functions similarly to GLAS by applying localized smoothing techniques to estimate trend and seasonal components, using adaptable polynomial fits to model both linear and nonlinear patterns.

2.2. Parametric Models

Some critics expressed concerns about nonparametric seasonal adjustment methods based on linear filters or moving averages. Slutsky (1927) and Yule (1927) noted the potential for these models to introduce artificial cycles, while others criticized the use of *ad hoc* empirical procedures when more rigorous mathematical tools were available. This growing dissatisfaction with nonparametric approaches led to the development of explicit model-based methodologies for seasonal adjustment. There are two main categories of these model-based approaches: (i) those that rely on deterministic frameworks, and (ii) those grounded in stochastic modeling.

Early model-based methods relied on regression analysis. Pioneering works by Fisher (1937) and Mendershausen (1939) used least squares to fit polynomials and isolate seasonality. The 1960s saw a rise in multiple regression techniques, driven by econometric model development and computing advancements. Notable contributions include works by Rosenblatt (1965) and Lovell (1963), which fit components using parametric functions and ordinary least squares. However, their inability to capture the stochastic nature of series has limited their use. Extensions with local regressions, like DAINTRIES (Fischer 1995) and BV4 (Nourney 1984), have seen some development, though they face limitations like phase shifts and identification problems.

Unlike deterministic methods, stochastic methods rely on specifying unobserved component ARIMA models and applying signal extraction techniques. A key direction is the ARIMA Model-Based (AMB) approach, which models the observed time series using a seasonal ARIMA model, while components are derived from the model's structure using spectral estimation techniques. Pioneering works in this area include contributions by Maravall and Pierce (1987), Bell (1984), Hillmer and Tiao (1982), and Burman (1980). However, while powerful, ARIMA models are susceptible to inaccuracies caused by outliers and may struggle to correctly estimate deterministic components. To address this limitation, developments like TRAMO-SEATS (Gómez and Maravall 1995) use the Wiener-Kolmogorov filter to extract the components from the spectrum of a fitted ARIMA model by minimizing the mean squared error between the estimated and actual components. Compared with X11, TRAMO-SEATS produces more stable seasonal components by using a canonical decomposition method that maximizes the variability of the irregular element while minimizing that of the seasonal factors. However, it relies heavily on a well-fitting ARIMA model, and results are particularly sensitive to parameter uncertainty, especially in very short or long time series.

2.3. Semiparametric Models

Building upon the work of Box and Jenkins (1970) on ARIMA models in the 1970s (see Box et al. 2015), Dagum (1980) proposed a new X11 variant called X11-ARIMA. This represented an improvement over the original X11 program and was further automated at Statistics Canada. The key improvement lies in X11-ARIMA's ability to extend predictions beyond the observed data and estimate values prior to the start of the series. This capability addresses missing data at the series' ends, allowing for less asymmetric filters. In contrast, the original X11 simply extrapolated missing values arbitrarily, leading to significant revisions when the missing data eventually became available. Another extension of X11 is the United Kingdom version, which incorporated forecasts based on the Kenny-Durbin autoregression technique (Kenny and Durbin 1982), though Fischer (1995) found that X11-ARIMA delivered more accurate forecasting results. The Dutch Central Bureau of Statistics also introduced an extension known as CPBX11 software

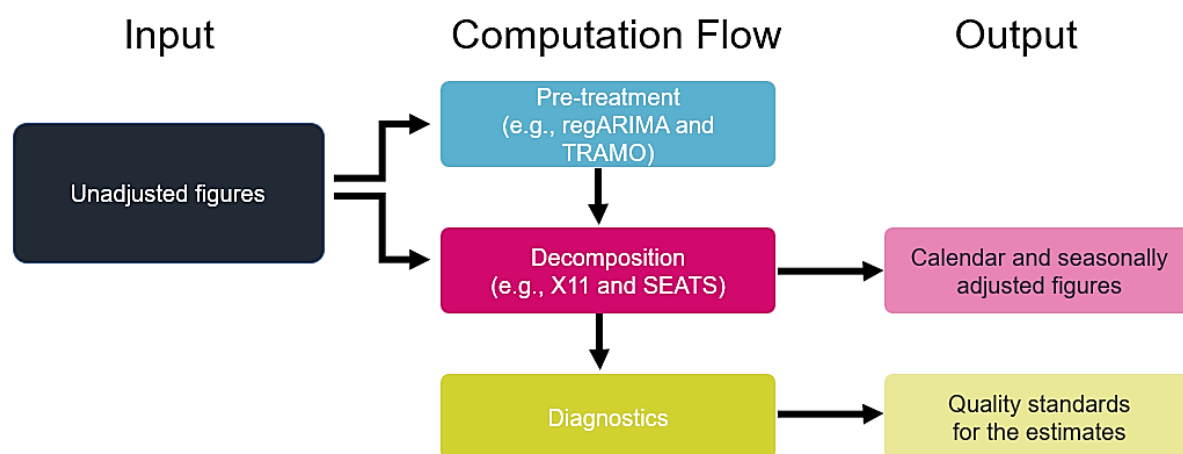
(Van der Hoeven and Hundepool 1986; Central Bureau of Statistics 1981), which merges functionalities from both the X11 method and the CPB-1 method developed by the Central Planning Bureau (Central Bureau of Statistics 1976).

The United States Bureau of the Census further advanced X11-style models with the development of X12-ARIMA. It draws heavily from the foundations of X11-ARIMA, as outlined in the works of Findley et al. (1998) and United States Bureau of the Census (2000). X12-ARIMA uses the core X11 methodology while integrating most of the improvements introduced in X11-ARIMA along with several new developments. The most significant one is the addition of a pre-treatment stage called RegARIMA. This pre-adjustment allows for simultaneous estimation of outliers, trading-day (or working-day) variations, and other calendar effects like Easter and leap year, using a seasonal ARIMA model. X12-ARIMA allows the user to define the model or to select it via an automatic procedure based on five models, and uses the model to extrapolate the original series. X12-ARIMA also incorporates additional seasonal and Henderson filters. Furthermore, it offers all the diagnostic tools found in X11-ARIMA for evaluating the quality of seasonal adjustment, along with new features such as spectral tests to assess seasonality and detect residual trading-day effects, as well as assessments of the stability of the seasonal adjustment.

3. METHODOLOGY

We followed a three-stage approach in the seasonal adjustment of QNA: (i) pre-adjustment, (ii) decomposition, and (iii) quality diagnostics.

Figure 2: Basic Framework of Seasonal Adjustment



Source: Eurostat (2018).

The first stage is pre-adjustment of data. The objective is to identify an ARIMA-based regression model that most accurately captures the features of the original series.

This involves detecting and correcting the series for data and/or component nonlinearities that could hamper the estimation of seasonality and calendar effects. The pre-adjustment stage primarily includes the selection of (i) the relationship between unobserved components (additive or multiplicative), (ii) order of the ARIMA model, (iii) calendar-related influences, and (iv) the treatment of outliers and other external variables.

(i) Specification of the relationship between unobserved components: The X11 decomposition primarily utilizes two models: additive and multiplicative. The additive model assumes independence between unobserved components, whereas the multiplicative model posits that the size of the unobserved component scales proportionally with the series level. JDemetra+ offers logarithmic transformation for multiplicative decomposition and no transformation for the additive model. For ARMSTAT data, we followed the ESS guidelines (2015), which recommend automatic transformation selection, but also an option for manual intervention for problematic series. To differentiate between transformations, we employed a test in X13-ARIMA-SEATS based on the Akaike Information Criterion (AIC). This involved fitting a RegARIMA model to both untransformed and transformed series, with the final decision based on the value of AIC.

(ii) The order of the ARIMA model: The subsequent stage in the pre-adjustment process involves selecting a RegARIMA model to represent the series. In this model, the average behavior of the series or its logarithm is modeled as a linear combination of explanatory variables, while the series' variability and correlation patterns are captured by an ARIMA process. We did not incorporate additional regressors beyond the built-in ones to model specific disruptions in the QNA series, as no significant methodological changes or events that could have caused structural breaks were identified. A RegARIMA model for pre-adjustment of series can be represented as follows:

$$\Phi(L)\Phi(L^s)(1-L)^d(1-L^s)^DY_t = \Theta(L)\Theta(L^s)\varepsilon_t,$$

where Y_t is the original series, L is the backshift lag operator ($Y_{t-1} = LY_t$), $\Phi(L)$ is the regular autoregressive (AR) operator with lag order p , $\Phi(L^s)$ corresponds to the seasonal autoregressive operator with lag order P , $\Theta(L)$ is the non-seasonal MA operator with lag order q , $\Theta(L^s)$ is the seasonal MA operator with lag order Q , s is the seasonal frequency, and ε_t is a white noise error term.

Identifying the model involves choosing the orders of AR and MA operators, both seasonal and non-seasonal (p, d, q)(P, D, Q). X13-ARIMA-SEATS employs a data-driven approach to determine the appropriate ARIMA model, beginning with a (0,1,1)(0,1,1) model, known as the "airline" model. This parsimonious model often provides a good fit for economic time series, and regression effects are identified and removed. Unit root tests determine the differencing orders (d and D). The (p,q)(P,Q) ARMA order is then identified by comparing statistical criteria across several models, up to a user-specified maximum order. Finally, residual diagnostics for the selected model are evaluated against the airline model for validation of the final model.

We start with the ARIMA model provided by X13-ARIMA-SEATS, followed by a review of residual diagnostics to expose possible misspecifications. Unless significant issues arise, we prefer the

automatic choice, understanding that the differencing orders (d and D) usually are either 0 (stationary component) or 1 (nonstationary component).

(iii) Calendar effects: We next remove calendar effects from the series as these can significantly hinder the accuracy of our decomposition into unobserved components. When a quarter contains an atypical number of working days, the time series measuring economic activities may exhibit a temporary spike owing to the increased time available for production. Linear models such as ARIMA are unable to account for calendar-related variations, leading to misclassification during the decomposition process and assigning these effects to the irregular component. Consequently, the adjusted series may show a misleading rise or decline that is actually caused by differing numbers of working days in the comparison periods.

To prevent this type of distortion, it is essential to estimate and eliminate calendar effects from the raw data before beginning the decomposition process. These effects are modelled using deterministic variables that precisely reflect changes in the calendar over time. The working-days effect is handled through a single regressor, which contrasts the number of working days (for example, Monday through Friday) against weekend days (such as Saturday and Sunday) according to the following equation:

$$wd_t = \left(\#Weekdays - \frac{5}{2} \#Weekend\ days \right),$$

where the factor is included to ensure that the working-days regressor averages to zero during a standard seven-day week.

This incorporates the assumption that weekdays generally have similar economic effects (in both direction and magnitude) that differ from those observed on weekend days. Any deviation from the standard week composition is captured within the regressor, where a value greater than 0 indicates that quarter t has more working days than a typical week. In Armenia, controlling for these effects is particularly important, given the uneven distribution of national holidays and days of remembrance across quarters, where the minimum number of working days in a quarter can be as low as 57, whereas the maximum can reach 66 (see Table 1).

Table 1: Nonworking Days in Armenia

Year	Q1	Q2	Q3	Q4	Nonworking Days	Status	Official Holidays
2012	59	60	64	65	31 December, 1–6 January	2009–2021	New Year
2013	57	60	66	65	31 December, 1–2, 6 January	From 2022	
2014	58	60	66	65	7 January	2009–2021	Mereloc
2015	58	61	65	65	None	From 2022	
2016	58	64	65	65	28 January	No change	Army Day
2017	59	61	64	65	8 March	No change	Women's Day
2018	59	60	64	65	24 April	No change	Genocide Memorial Day
2019	57	60	66	65	1 May	No change	Labor Day

Continued on the next page

Year	Q1	Q2	Q3	Q4	Nonworking Days	Status	Official Holidays
2020	59	61	65	65	9 May	No change	Victory Day
2021	57	64	65	65	28 May	No change	Republic Day
2022	61	64	65	65	5 July	No change	Constitution Day
2023	60	60	64	64	21 September	No change	Independence Day

Source: Law on Holidays and Memorial Days of the Republic of Armenia.

arlis.am/DocumentView.aspx?docid=102931.

In addition to conventional calendar effects, we also control for the Easter effect, which can shift between March (Q1) and April (Q2) in a given year. To account for this, an Easter regressor is used, which measures the share of days before Easter within March and April. Once the length of the Easter effect is established, the regressor is defined as:

$$e_t = \left(\frac{WD_t}{wd} - \overline{WD} \right),$$

where WD_t represents the number of working days in quarter t and \overline{WD} is the average share of working days in that quarter. Usually, \overline{WD} is approximated as 0.5 for both the first and second quarters, implying that the Easter effect days are evenly split between these two periods.

Finally, we control for the leap year effect using a regressor that accounts for the extra day in February of leap years. The regressor is assigned a value of 0.75 if t is in February of a leap year, -0.25 if t is in February of a nonleap year, and 0 otherwise. This regressor establishes a 4-year cycle with a peak in February of leap years. Over the full cycle, the positive effect of the leap year is offset by the negative effects in the following nonleap years.

(iv) Outliers and other intervention variables: The final stage of pre-adjustment is detecting and adjusting outliers to minimize their influence on the decomposition process. This step is crucial because outliers, if left unaddressed, can significantly distort the underlying trend and seasonal patterns in the series. X13-ARIMA-SEATS offers an automated outlier detection procedure that utilizes dummy variables within a specified timeframe. This procedure calculates coefficients for various outlier types and incorporates those with statistically significant t-statistics into the model. We generally follow the automatic outlier detection approach outlined in ESS (2015) guidance point 2.7. However, for specific events, this approach may not be suitable, as outliers can be challenging to identify, particularly during times of significant economic shifts like recessions. A prominent example is the COVID-19 pandemic, which significantly impacted economic activity worldwide in a way that is not reflected in historical data. In such cases, detecting and adjusting outliers becomes even more challenging as a result of the limited availability of future observations needed to fully understand the event's nature. For events like COVID-19, we adopted a manual approach to outlier detection and adjustment; this is discussed in detail in Section 6.

For the decomposition method, we adopted the X13-ARIMA-SEATS approach, which integrates both X11-type and SEATS filters within a single program. This allows for a straightforward comparison of series with different features by applying a uniform set of diagnostic measures. Our choice is based on extensive experience and expertise of ARMSTAT staff, who have employed the X11 methodology since 1998 and X12-ARIMA since 2013. Additionally, this

approach aligns with recent standards and recommendations in time series analysis, particularly the ESS guidelines (2015) and IMF recommendations.

The X11 filter is an iterative process that applies a series of predetermined moving average filters. After the series is pre-adjusted (including backcasting and forecasting), it undergoes three rounds of filtering, each with adjustments for extreme values, known as the B, C, and D iterations. Additionally, the X11 filter incorporates an algorithm designed to minimize the influence of outliers during adjustment. This algorithm identifies extreme values through statistical analysis of the seasonal-irregular (SI) ratios and temporarily replaces them with average values during the B and C stages. Table 2 provides an overview of the main steps in this procedure.

Table 2: X13-ARIMA-SEATS Algorithm

Step 1	Calculate the trend using a 2×4 MA	$TC_t^{(1)} = M_{2 \times 4}(X_t)$
Step 2	Compute the SI component	$(S_t + I_t)^{(1)} = X_t - TC_t^{(1)}$
Step 3a	Derive the seasonal component by applying a 3×3 MA for each month	$S_t^{(1)} = M_{3 \times 3}[(S_t + I_t)^{(1)}]$
Step 3b	Normalize the seasonal component using a 2×4 MA	$\tilde{S}_t^{(1)} = S_t^{(1)} - M_{2 \times 4}(S_t^{(1)})$
Step 4	Calculate the seasonally adjusted series	$SA_t^{(1)} = (TC_t + I_t)^{(1)} = X_t - \tilde{S}_t^{(1)}$
Step 5	Estimate the trend component using a 13-term Henderson MA	$TC_t^{(2)} = H_{13}(SA_t^{(1)})$
Step 6	Compute the SI component again	$(S_t + I_t)^{(2)} = X_t - TC_t^{(2)}$
Step 7a	Determine the seasonal component by applying a 3×5 MA for each month	$S_t^{(2)} = M_{3 \times 3}[(S_t + I_t)^{(2)}]$
Step 7b	Normalize the seasonal component using a 2×4 MA	$\tilde{S}_t^{(2)} = S_t^{(2)} - M_{2 \times 4}(S_t^{(2)})$
Step 8	Estimate the final seasonally adjusted series	$SA_t^{(2)} = (TC_t + I_t)^{(2)} = X_t - \tilde{S}_t^{(2)}$

MA = moving average, SI = seasonal-irregular.

Source: Eurostat (2018).

4. FINDINGS

In an ideal scenario, seasonally adjusted QNA series should retain the accounting relationships inherent in the original data. However, owing to nonlinearities inherent in seasonal adjustment procedures, inconsistencies may arise across variables and frequencies. This section explores the results of applying seasonal adjustment methods to Armenian QNA data, addressing key issues such as (i) direct versus indirect adjustment of aggregates; (ii) update strategies; (iii) revision period; and (iv) the interaction among volume, price, and value indices in seasonally adjusted data.

4.1. Comparison of Direct and Indirect Approaches to Seasonal Adjustment

Seasonal adjustment of aggregate series can be performed in two ways: by directly adjusting the overall aggregate or by first adjusting the individual components and then summing them to form the aggregate. In the context of QNA, a seasonally adjusted GDP estimate might be obtained by adjusting GDP directly or by summing the seasonally adjusted series of value-added by economic activity and net taxes on products. This principle also applies when compiling GDP from the expenditure side.

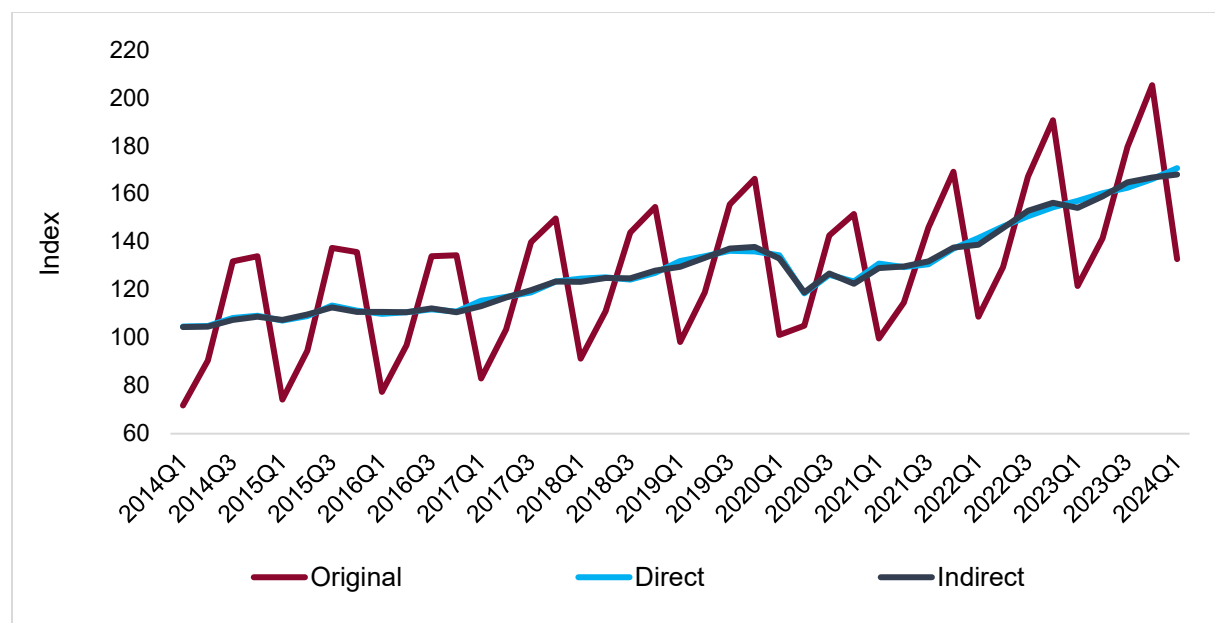
Conceptually, neither the direct nor the indirect approach holds an inherent advantage. For aggregates, the direct approach may yield superior results when component series exhibit similar seasonal patterns and possess highly correlated trend cycles. Aggregation, in this case, often lessens the impact of irregular fluctuations within component series, which might otherwise hinder proper seasonal adjustment at the most granular level. This effect can be particularly pronounced in small open economies like Armenia, where irregular events exert a stronger influence on data. Conversely, the indirect approach may be optimal when component series display vastly divergent seasonal patterns. Here, aggregation can create large, volatile seasonality, obscuring stable effects and complicating the identification of seasonality within the aggregate series. Additionally, breaks, outliers, and calendar effects may be detectable more readily in detailed series than directly from aggregates, as they often present simpler and more economically interpretable patterns at the disaggregated level. While adjusting data at a more granular level can be beneficial, it may lead to remaining seasonal patterns in the aggregated series, create less stable seasonally adjusted outputs, and increase the likelihood of future revisions.

In Figure 3, we compare original and seasonally adjusted chain-linked volume indices calculated using both direct and indirect approaches, while Figure 4 shows the respective year-on-year growth rates. The process of deriving indirectly seasonally adjusted aggregate series involved (i) seasonally adjusting the chain-linked component series, (ii) reversing the chain-linking to obtain unchained values, (iii) aggregating the adjusted components, (iv) reapplying the chain-linking process to the aggregate, (v) re-referencing the seasonally adjusted aggregate series to the index reference year, and (vi) ensuring that the total for the year remained consistent between the seasonally and calendar-adjusted series and the calendar-adjusted series alone. While both approaches generally produce similar trends, notable discrepancies emerge in certain periods. For instance, while the average relative difference in year-on-year growth rates remains close to 0, deviations of up to 1.0 percentage point occur in some quarters. This underscores the importance of a careful choice between direct and indirect methods when working with Armenian QNA data.

To guide the selection between direct and indirect seasonal adjustment methods, we first examine the correlations among the trend-cycle components of sectoral value-added, as presented in Figure 5. The letters in the figure correspond to the NACE (statistical classification of economic activities in the European Community) sectors, whose descriptions can be found in Appendix A. Positive correlations are depicted by blue circles; negative correlations are shown in red. The intensity of the color reflects the strength of the correlation: darker hues indicate stronger correlations, whether positive (dark blue) or negative (dark red), whereas lighter hues represent weaker correlations. Blank cells indicate statistically insignificant correlations at the 1% significance level. Notably, some sectors exhibit highly correlated economic activity, such as the strong correlation between accommodation and food service activities (I) and real estate activities

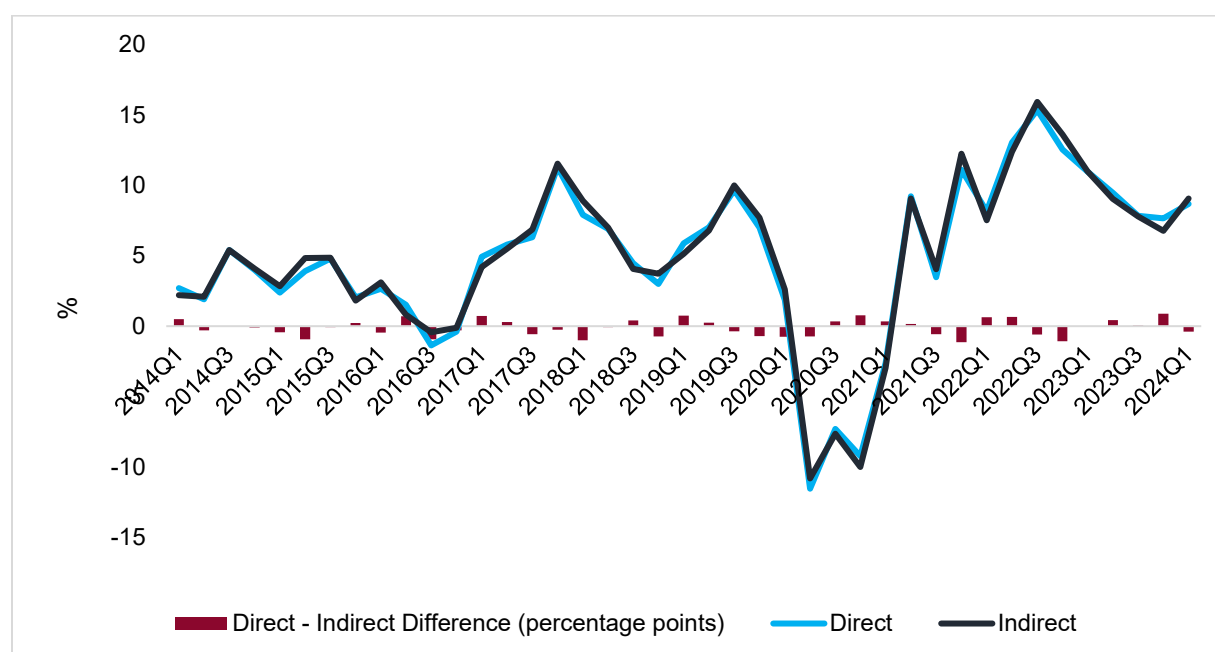
(L). However, most trend-cycle components show insignificant correlations. This suggests that directly adjusting GDP may mask important seasonal variations within individual sectors, potentially compromising the quality of the seasonally adjusted GDP.

Figure 3: Chain-Linked Volume Indices (2012 = 100)



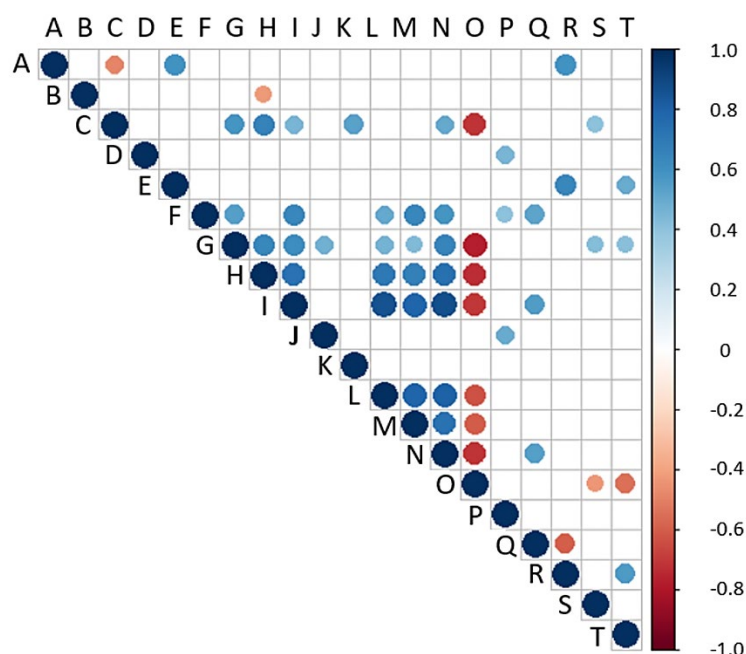
Source: Authors' calculations based on QNA data from ARMSTAT.

Figure 4: Year-on-Year Growth Rates of Gross Domestic Product



Source: Authors' calculations based on QNA data from ARMSTAT.

Figure 5: Correlation Matrix of Trend-Cycle Components of Sectoral Value-Added



Source: Authors' calculations.

To further investigate the implications of these methods, we conducted a revision analysis on year-on-year GDP growth rates. We employed a recursive estimation approach over the period from 2013Q1 to 2022Q4 and subsequently incorporated additional data points up to 2023Q4. The resulting revisions for 2021, 2022, and 2023 indicate that both direct and indirect methods introduce changes to the seasonally adjusted GDP series. However, the magnitude of revisions tends to be marginally larger under the indirect method, which is evidenced by the higher Mean Squared Error (MSE) values for indirect adjustment across analyzed periods. The larger revisions under the indirect approach likely result from the amplification of noise and inconsistencies arising from the independent adjustment of component series. In contrast, the direct method, which operates on aggregate data, may benefit from a smoothing effect, leading to more stable estimates. Despite the higher revision susceptibility of the indirect method, we preferred it for Armenia, given the potential for divergent seasonal patterns among GDP components and the strong user demand for preserving accounting and aggregation relationships in the QNA data.

Table 3: Comparison of Revisions Under Direct and Indirect Seasonal Adjustment

(year-on-year changes in seasonally adjusted gross domestic product)

	2021				2022				2023				
	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	Q1	Q2	Q3	Q4	
Direct Adjustment													
Until													MSE
2022Q4	-2.5	9.2	3.4	11.1	8.3	13.1	15.2	12.5					0.86
2023Q1	-2.5	9.3	3.4	11.1	8.3	13.1	15.2	12.5	11.2				
2023Q2	-2.5	9.3	3.4	11.1	8.3	13.1	15.2	12.5	11.2	9.5			
2023Q3	-2.6	9.2	3.5	11.1	8.2	13.0	15.3	12.5	11.1	9.4	7.8		
2023Q4	-2.6	9.2	3.5	11.1	8.2	13.1	15.4	12.5	11.0	9.5	7.8	7.6	
Indirect Adjustment													
Until													MSE
2022Q4	-2.5	8.6	3.9	12.4	7.9	12.0	15.8	13.9					1.21
2023Q1	-2.8	8.7	4.0	12.4	7.7	12.1	15.7	13.8	11.3				
2023Q2	-2.9	8.9	3.9	12.4	7.7	12.3	15.7	13.8	11.3	9.0			
2023Q3	-2.9	9.0	3.8	12.4	7.6	12.4	15.7	13.8	11.3	8.9	7.5		
2023Q4	-2.9	9.0	4.1	12.1	7.8	12.4	15.9	13.5	11.4	9.1	7.8	6.6	

MSE = mean squared error.

Source: Authors' calculations.

4.2. Strategies for Updating Seasonal Adjustment

Seasonal adjustment procedures can follow different updating approaches, depending on the frequency with which the adjustment models and their settings are re-evaluated as new or revised data become available. Two main approaches are mostly used: concurrent or current adjustment.

In the concurrent approach, the model, its configuration, and parameters are re-estimated every time new or revised data points are added. This ensures that the adjusted series reflect the latest seasonal patterns and structural changes, typically resulting in the most accurate estimates. However, this strategy tends to produce more frequent revisions to the adjusted data due to ongoing updates to the underlying model and parameters. In contrast, the current adjustment approach updates the model and its components only during predetermined review windows – usually held annually or when significant changes occur in the source data. Between these review periods, the model structure and estimated parameters remain unchanged. Adjusted values are generated by applying projected seasonal and calendar factors to the incoming data. As a result, revisions to the seasonally adjusted series are concentrated within the review periods, with no adjustments made during the interim unless historical source data are modified.

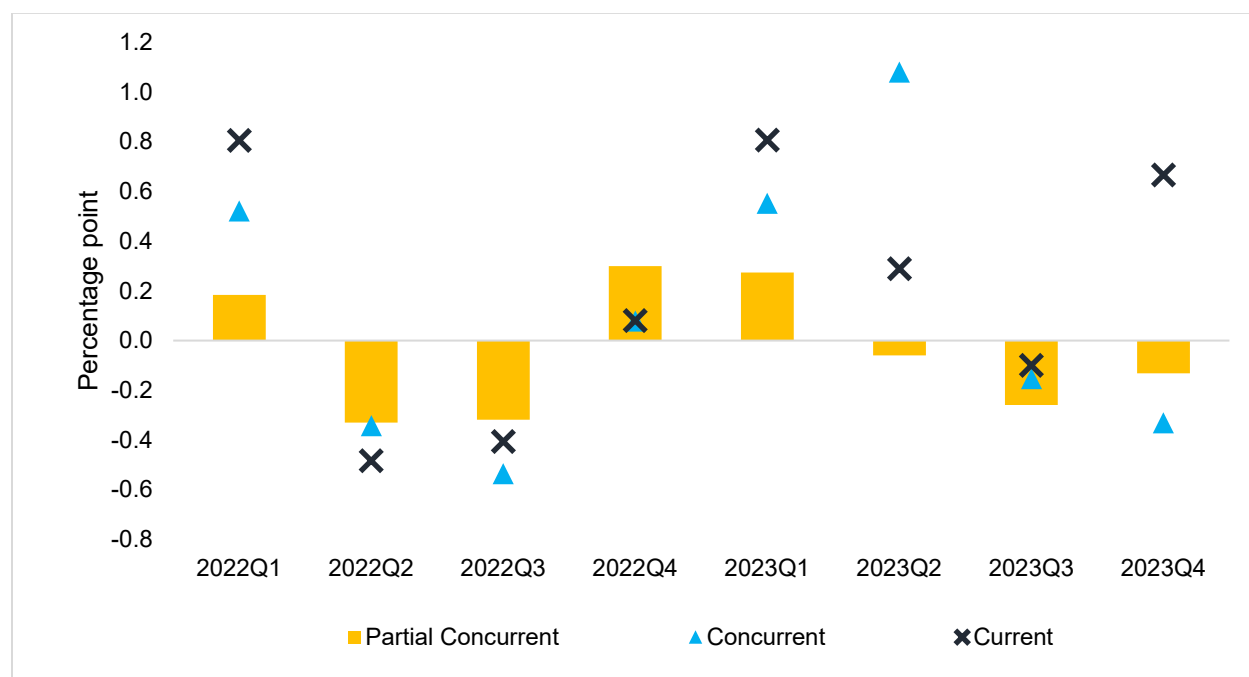
A compromise between the concurrent and current seasonal adjustment strategies is the partial concurrent approach. In this method, the choice of models and adjustment settings is fixed during

scheduled review periods – usually once per year or following substantial data revisions – and remains constant until the next review. However, the parameters of the model are re-estimated every time the series is updated with new data. While the model and adjustment settings are generally kept unchanged between reviews, they may be revised in response to rare or exceptional circumstances that demand special treatment. Outside of such events, any revisions to the seasonally adjusted data arise solely from the updated parameter estimates. This strategy offers a balanced approach by maintaining a high level of accuracy in the adjustments while reducing the frequency and magnitude of revisions.

In Figure 6, we compare the magnitudes of revisions to year-on-year GDP changes across the three approaches. As anticipated, the partial concurrent method generates fewer revisions in estimates compared to the current and concurrent approaches, which lead to larger revisions. For instance, the second quarter of 2023 experienced a 0.3 percentage point revision in the year-on-year GDP change using the current approach, a more substantial 1.1 percentage point revision with the concurrent approach, and a minor -0.1 percentage point revision with the partial concurrent approach. Consequently, ARMSTAT adopted this latter method for seasonally adjusting QNA in Armenia. The model, filters, and outliers within this approach are revised annually, while seasonal factors and calendar effects are updated with each new data release. This approach aligns with the ESS guidelines and the IMF manual on QNA, both of which recommend partial concurrent adjustment to account for new information and minimize the size of revisions resulting from the seasonal adjustment process.

Figure 6: Current Versus Concurrent Versus Partial Concurrent Adjustment

(revisions to year-on-year gross domestic product growth rates, percentage points)



Source: Authors' calculations.

4.3. Revision Period

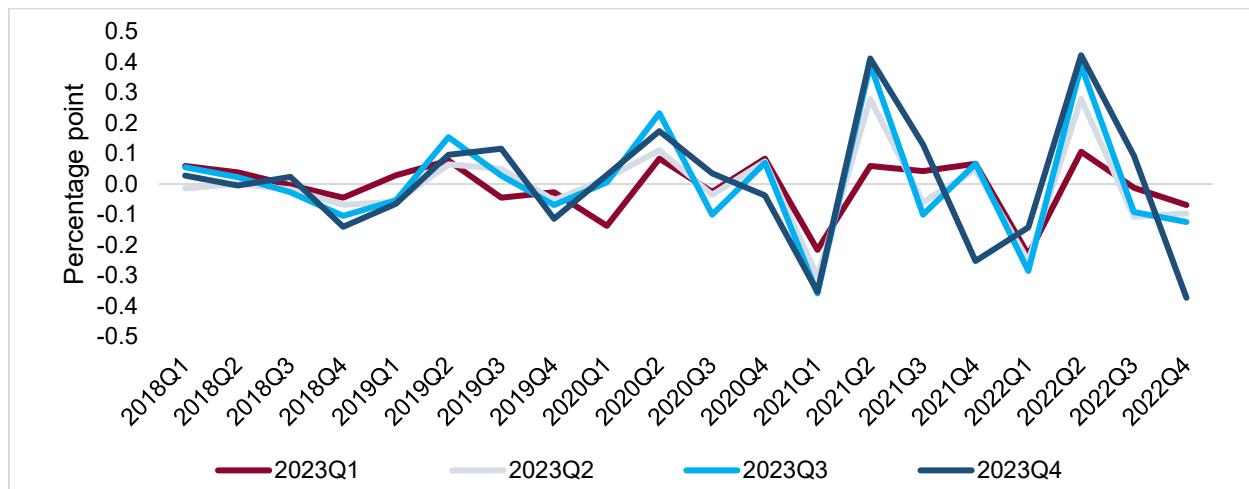
Another critical aspect of revisions policy is determining the revision period for QNA publications, which defines the number of previously released quarterly observations subject to revision. In a partial concurrent approach, the entire seasonally adjusted series is modified whenever a new observation is added or an existing one is revised. Revisions can be substantial for years near the last revised observation in the original series, but tend to be minor for more distant observations. This pattern arises because seasonal adjustment filters assign greater weight to recent observations compared to those further in the past.

According to the IMF's QNA manual, a partial concurrent adjustment strategy mandates revising seasonally adjusted series for at least 2 complete years prior to modifying the original data. This period enables the inclusion of updated regression coefficients and newly detected outliers into the latest seasonally adjusted data. Maintaining a minimum of 2 full years is crucial for accurately calculating quarter-to-quarter growth rates for the current and preceding year using consistently adjusted data. Seasonally adjusted data published before this 2-year window can remain unchanged unless artificial breaks emerge in the series. Similarly, the ESS guidelines recommend setting the starting point for the earliest seasonally adjusted data revision at the beginning of a year, 3 years before the unadjusted data revision period.

To determine an appropriate revision period for Armenia, Figure 7 compares revisions to year-on-year GDP growth rates following the addition of new observations for each quarter of 2023. The analysis reveals that, while recent data significantly impacts the most recent estimates, earlier observations remain relatively stable. Based on these findings, ARMSTAT adopted a revision policy that updates the previous 3 years of data with each new observation, while preserving estimates for earlier periods. The only exception to this revision policy occurred when ARMSTAT transitioned to a new seasonal adjustment framework at the end of 2022. During this period, the entire series was updated compared to the previous methodology, aligning with ESS recommendations for major revisions.

Figure 7: Changes in Seasonally Adjusted Estimates by Adding New Observations

(revisions to year-on-year gross domestic product growth rates, percentage points)



Source: Authors' calculations.

4.4. Relationship Between Price, Volume, and Value Indices for Seasonally Adjusted Series

Seasonally adjusted estimates for national accounts price indices, volume measures, and current price data can be obtained by either adjusting each series independently or adjusting two and deriving the third as a residual, assuming all three exhibit seasonal patterns. Given nonlinearities in seasonal adjustment processes, these methods produce different results, although the differences are typically minor. As the IMF suggests, deciding which series to derive residually should be determined on a case-by-case basis based on which approach yields the most reasonable outcome.

Theoretically, seasonality in current price data is generated by seasonality from price and volume effects. Therefore, the best approach appears to be applying seasonal adjustment to the price and volume series and then indirectly deriving seasonally adjusted data in current prices. However, directly adjusting data in current prices may be preferred when the main data source is available in nominal terms.

Before 2022, ARMSTAT seasonally adjusted only the volume indices. However, since adopting the new framework, both volume measures and current price data are seasonally adjusted, while price deflators are derived as residuals. This decision is influenced by the fact that the underlying data for QNA is collected in nominal terms in Armenia, and volume indices are subsequently derived using QNA series at the previous year's prices through the double deflation method.

5. QUALITY DIAGNOSTICS

In this section, we evaluate the quality of the seasonally adjusted series using both parametric and nonparametric criteria. To verify the absence of residual seasonality, we begin by conducting seasonality tests on the directly adjusted series and their irregular components. The residual seasonality tests used in JDemetra+ are derived from the set of diagnostics originally created for X12-ARIMA. Among these, we primarily rely on the F-test, which uses seasonal dummy variables (including a mean effect and three seasonal dummies for quarterly data) to determine whether they are jointly statistically insignificant.

The rejection thresholds and test results for this analysis are presented in Tables 4a and 4b. As indicated, the p-values for most series exceed 0.05, confirming the absence of residual seasonality in the individual GDP components. Since the seasonally adjusted QNA series are derived indirectly by aggregating the corresponding subcomponents, we also perform similar tests on the aggregated series. As shown in Appendix C, all aggregated series are free from residual seasonality. Additionally, we conduct analogous tests on the price deflators calculated from seasonally adjusted volume measures and current price data, with results in Appendix C supporting that these series are also devoid of residual seasonality.

Table 4a: Critical Values for Interpreting F-Test Results

P-value	JDemetra+ default settings
<0.01	Severe
[0.01, 0.05)	Bad
[0.05, 0.1)	Uncertain
≥0.1	Good

Source: JDemetra+ Reference Manual (<https://jdemetradocumentation.github.io/JDemetra-documentation/>).

Table 4b: Results of the F-Test for the Presence of Residual Seasonality and Trading-Day Effects

NACE Code	Residual Seasonality		Residual Trading-Day Effects	
	Seasonally adjusted series	Irregular component	Seasonally adjusted series	Irregular component
A	Good (0.668)	Good (0.418)	Good (0.079)	Good (0.405)
B	Good (0.921)	Good (0.832)	Good (0.101)	Good (0.134)
C	Good (0.477)	Good (0.446)	Good (0.429)	Good (0.269)
D	Good (0.513)	Good (0.635)	Good (0.905)	Good (0.058)
E	Good (0.768)	Good (0.569)	Good (0.207)	Good (0.779)
F	Good (0.321)	Good (0.222)	Good (0.172)	Good (0.650)
G	Good (0.382)	Good (0.187)	Good (0.493)	Good (0.091)
H	Good (0.985)	Good (0.781)	Good (0.639)	Good (0.240)
I	Good (0.959)	Good (0.568)	Good (0.607)	Good (0.292)
J	Good (0.895)	Good (0.973)	Good (0.371)	Good (0.598)
K	Good (0.938)	Good (0.541)	Good (0.966)	Good (0.328)
L	Good (0.953)	Good (0.958)	Good (0.804)	Good (0.436)
M	Good (0.898)	Good (0.403)	Good (0.255)	Good (0.756)
N	Good (0.728)	Good (0.487)	Good (0.235)	Uncertain (0.024)
O	Good (0.422)	Good (0.446)	Good (0.059)	Good (0.124)
P	Good (0.812)	Good (0.477)	Good (0.131)	Good (0.976)
Q	Good (0.717)	Good (0.633)	Good (0.216)	Good (0.304)
R	Good (0.814)	Good (0.557)	Good (0.160)	Good (0.059)
S	Good (0.593)	Good (0.397)	Good (0.489)	Good (0.799)
T	Good (0.723)	Good (0.781)	Good (0.091)	Uncertain (0.017)

Source: Authors' calculations.

We next evaluate the specified RegARIMA models from the pre-adjustment phase using several tests for normality, independence, randomness, and linearity of residuals. Ensuring residuals are normally distributed is important for the accuracy of forecast prediction intervals. To test this, we use the Doornik-Hansen test, which evaluates skewness and kurtosis in multivariate data transformed to achieve independence. The corresponding p-values from this test are presented in column (1) of Table 5. The findings show that residuals from all RegARIMA models conform to a normal distribution, indicating no additional model refinement is required.

To check the independence of residuals, we apply the Ljung-Box and Box-Pierce Q-statistics, calculated for both regular and seasonal lags. The regular lag tests evaluate autocorrelation over the first 16 lags, while seasonal lag tests focus on the first two seasonal lags. Assuming the residuals are random, their test statistics should follow a chi-square distribution, with degrees of freedom equal to the number of model parameters. The results of these tests are shown in columns (2) and (3) of Table 5. Since most p-values exceed 0.05, we do not reject the null hypothesis that residuals are independently and identically distributed, supporting the independence assumption.

The randomness of the residuals' signs is evaluated using the Wald-Wolfowitz test, also called the Run test. This test analyzes data centered on the mean by counting the number and length of runs – defined as consecutive values all above or all below the mean. An up run consists of successive values above the mean, while a down run consists of successive values below it. The test examines whether these up and down runs are evenly distributed over time, since both an excess and a shortage of runs are unlikely in truly random sequences. It also tests whether the lengths of these runs occur randomly. The outcomes shown in columns (4) and (5) of Table 5 demonstrate that, in our case, the residuals exhibit randomness both in terms of the number of runs around the mean and their average length.

Finally, the linearity of residuals test provides evidence of whether there is autocorrelation in residuals or not. Significant values of the Ljung-Box and Box-Pierce Q-statistics of the squared residuals indicate random variation in the coefficients or time-varying conditional variances, leading to lower reliability of the test statistics and forecast coverage intervals. The results in columns (6) and (7) of Table 5 show that, in our dataset, the null hypothesis of no autocorrelation cannot be rejected, which means the residuals do exhibit a linear structure.

Table 5: P-Values of RegARIMA Residual Tests

NACE Code	Normality	Independence		Randomness		Linearity	
	Doornik-Hansen	Ljung-Box	Box-Pierce	Runs around mean number	Runs around mean length	Ljung-Box on squared residuals	Box-Pierce on squared residuals
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
A	0.765	0.753	0.903	0.901	1.000	0.893	0.972
B	0.947	0.543	0.753	0.989	1.000	0.623	0.802
C	0.712	0.637	0.894	0.205	1.000	0.616	0.886
D	0.903	0.587	0.824	0.368	1.000	0.047	0.202
E	0.797	0.943	0.989	0.871	1.000	0.365	0.616
F	0.540	0.971	0.993	0.796	1.000	0.061	0.278
G	0.218	0.867	0.964	0.510	1.000	0.767	0.937
H	0.567	0.586	0.820	0.300	1.000	0.469	0.707
I	0.911	0.473	0.743	0.407	1.000	0.581	0.803
J	0.954	0.562	0.821	0.067	0.984	0.680	0.843
K	0.430	0.915	0.985	0.698	1.000	0.737	0.907
L	0.230	0.911	0.959	0.447	1.000	0.966	0.990
M	0.585	0.075	0.307	0.950	1.000	0.824	0.931
N	0.844	0.648	0.884	0.203	1.000	0.455	0.709

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NACE Code	Normality	Independence		Randomness		Linearity	
	Doornik-Hansen	Ljung-Box	Box-Pierce	Runs around mean number	Runs around mean length	Ljung-Box on squared residuals	Box-Pierce on squared residuals
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
O	0.401	0.836	0.935	0.638	1.000	0.003	0.057
P	0.275	0.357	0.621	0.003	0.023	0.792	0.931
Q	0.813	0.442	0.683	0.531	1.000	0.130	0.372
R	0.703	0.091	0.292	0.183	1.000	0.403	0.630
S	0.244	0.600	0.847	0.948	1.000	0.136	0.456
T	0.236	0.348	0.652	0.901	1.000	0.888	0.961

Source: Authors' calculations.

After ensuring all of the critical assumptions are satisfied in the pre-treatment stage, we analyze the quality of the seasonal adjustment results using a set of “M diagnostics” produced by JDemetra+. The various indicators assess different aspects of the seasonal adjustment process, such as how much the irregular component contributes to the overall variance (M1, M2, and M3), the randomness of the irregular component (M4), the significance of changes in the trend and irregular components (M5), the ratio of annual changes in the irregular component to the seasonal component (M6), the presence of identifiable seasonality (M7), and the stability of short- and long-term variations (M8, M9, M10, and M11). In addition, JDemetra+ produces two composite indicators (Q and Q – M2), which assess the overall quality of the models. Values exceeding 1 suggest possible problems with the adjustment, while values ranging from 0 to 1 are considered satisfactory.

The M-diagnostic indicators for all sectors, presented in Table 6, suggest the seasonal adjustment process is generally satisfactory for most sectors. However, a few sectors exhibit potential issues in specific indicators. In particular, some sectors, like mining and quarrying (B), manufacturing (C), and information and communication (J), have problems with moving seasonality, as indicated by M10 and M11 statistics exceeding the acceptable value of 1. Similarly, several sectors have a high irregular component, such as real estate activities (L), administrative and support service activities (N), and other service activities (S). However, for all sectors, the two composite indicators have values less than 1, confirming that, overall, the seasonal adjustment process appears to be adequate.

Table 6: The M-Diagnostics

NACE Code	M1	M2	M3	M4	M5	M6	M7	M8	M9	M10	M11	Q	Q-M2
A	0.0	0.0	1.3	1.2	1.0	1.2	0.1	0.3	0.2	0.3	0.3	0.5	0.5
B	0.6	0.1	0.2	0.5	0.2	0.3	0.6	1.0	0.7	1.5	1.4	0.5	0.6
C	0.1	0.1	0.5	0.2	0.7	0.9	0.3	0.8	0.6	1.5	1.5	0.5	0.5
D	0.7	0.4	1.3	0.6	1.3	0.8	0.4	1.4	0.8	1.6	1.6	0.9	0.9
E	0.8	0.1	0.6	0.5	0.5	0.5	0.4	0.8	0.5	0.8	0.7	0.5	0.6
F	0.0	0.0	0.3	0.6	0.6	1.1	0.1	0.3	0.2	0.5	0.4	0.3	0.3
G	0.0	0.0	0.0	0.3	0.2	1.0	0.3	0.5	0.5	0.4	0.4	0.2	0.3
H	0.8	0.3	0.4	0.9	0.4	0.9	0.2	0.2	0.1	0.2	0.2	0.4	0.4
I	0.1	0.0	0.0	0.2	0.2	0.7	0.3	0.7	0.1	0.6	0.4	0.2	0.2
J	1.1	0.2	0.3	0.7	0.2	0.1	0.4	1.1	0.9	1.2	1.2	0.6	0.6
K	0.1	3.0	0.0	0.7	0.2	0.3	0.4	1.1	0.4	0.9	0.7	0.7	0.4
L	1.2	0.9	1.0	0.5	1.0	0.5	0.5	1.2	0.9	1.6	1.5	0.9	0.9
M	0.3	0.3	0.9	0.3	0.7	0.3	0.3	0.6	0.3	0.9	0.9	0.5	0.5
N	0.7	1.1	1.2	1.0	1.0	0.1	0.3	0.6	0.2	0.7	0.7	0.7	0.6
O	0.7	0.8	1.8	0.3	1.5	0.1	0.4	0.8	0.7	0.4	0.4	0.7	0.7
P	0.1	0.1	1.1	1.2	0.9	0.3	0.2	0.4	0.3	0.4	0.4	0.5	0.5
Q	0.3	0.2	0.8	0.6	0.9	0.5	0.3	0.9	0.6	0.7	0.7	0.6	0.6
R	0.2	0.0	0.0	0.7	0.2	0.9	1.0	2.1	0.5	2.1	2.0	0.7	0.8
S	1.2	0.5	1.0	0.7	0.9	0.1	0.4	0.9	0.3	0.8	0.4	0.7	0.7
T	0.1	0.1	0.9	0.2	0.8	0.3	0.1	0.4	0.3	0.7	0.7	0.4	0.4

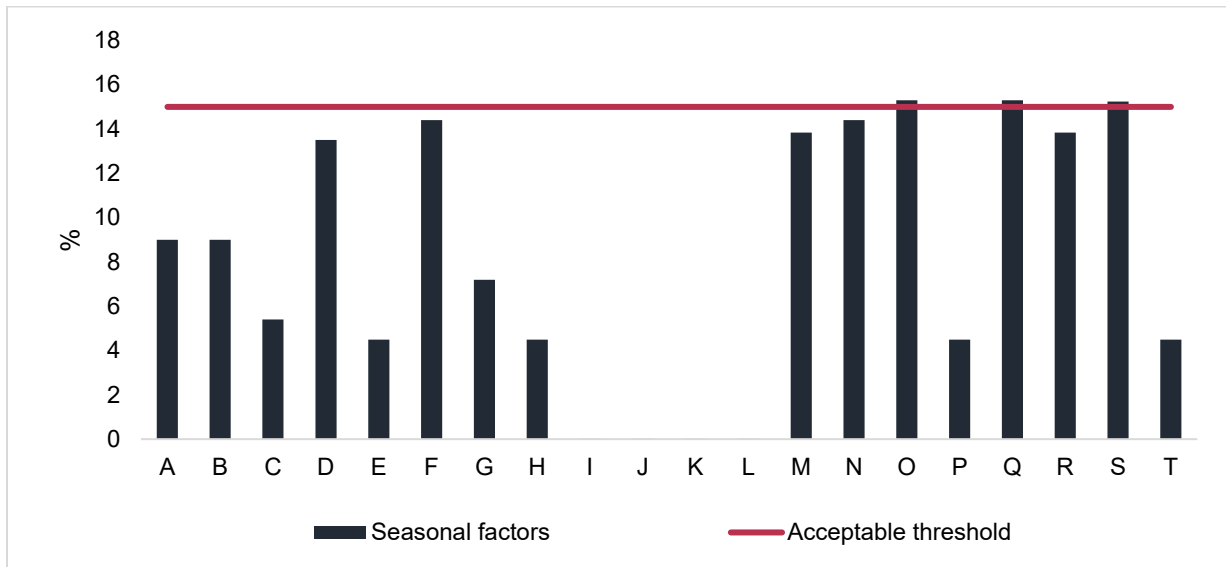
Source: Authors' calculations.

Seasonally adjusted time series should remain consistent, showing minimal variation when a few observations are added or removed from the original data. To evaluate this stability, we use sliding spans analysis, which examines how seasonal adjustment results fluctuate when different portions of the original dataset are used. This method specifically assesses the estimated seasonal factors and the quarter-to-quarter changes in the seasonally adjusted series, providing warnings if there is too much variability for the same quarter or if the count of unstable seasonal factors or changes surpasses acceptable thresholds.

In JDemetra+, a threshold of 3% of the test statistics is used to identify abnormal values. Following IMF guidelines, seasonal adjustment results are deemed stable when unstable seasonal factors account for less than 15% of all observations, and when abnormal quarter-to-quarter variations in the seasonally adjusted series represent less than 35% of the total observations. This is also consistent with the recommendations of Findley et al. (1990), who provide similar acceptable thresholds for these measures. Figures 8a and 8b show the share of abnormal seasonal factors and quarter-to-quarter changes, respectively, in the case of Armenian QNA series. As can be seen, in most cases, these shares are below the respective thresholds, meaning the seasonal adjustment results remain roughly constant in different specifications with varying numbers of observations.

Figure 8a: Abnormal Seasonal Factors

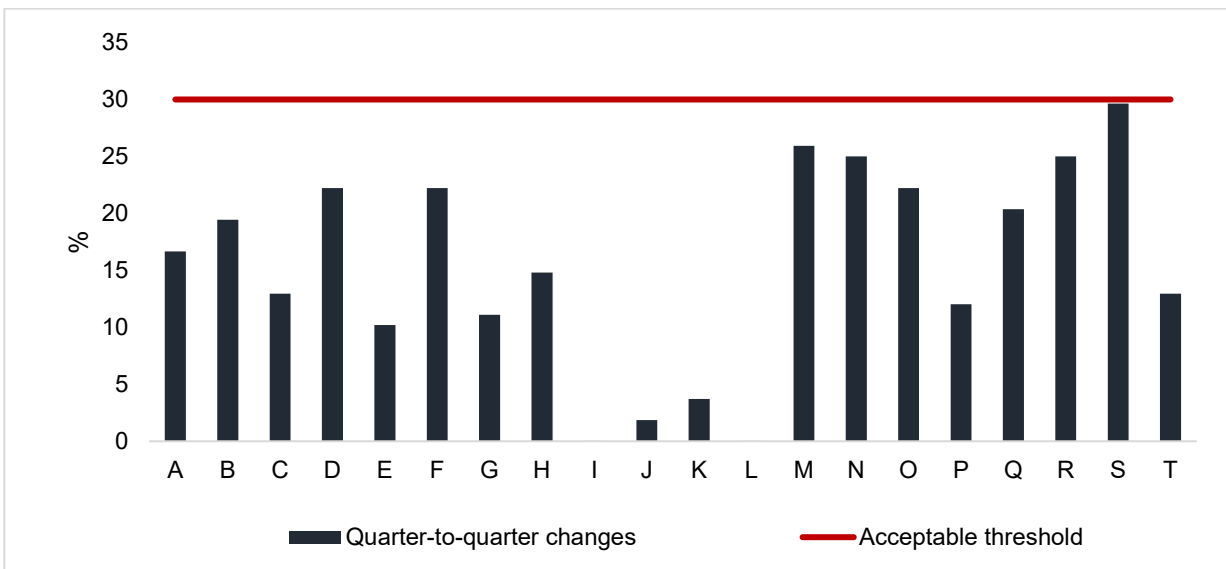
(% of total number of observations)



Source: Authors' calculations.

Figure 8b: Abnormal Quarter-to-Quarter Changes in Seasonally Adjusted Data

(% of total number of observations)



Source: Authors' calculations.

6. PRE-ADJUSTMENT OF QNA DURING THE COVID-19 CRISIS

The COVID-19 outbreak had a severe impact on the Armenian economy, leading to a GDP contraction of 7.2% in 2020. Statistically, this crisis introduced challenges in analyzing the endpoint of time series, for several reasons. First, estimating a level shift at the first data point was impossible since the series level prior to the given data was unknown. Second, a level shift at the last data point could not be distinguished from an additive outlier, and a temporary change at the last data point could also be mistaken for an additive outlier.

These inherent conceptual constraints pose challenges in accurately estimating the trend-cycle and irregular components. For instance, a level shift occurring near the end of a series might be mistakenly classified as an additive outlier, causing it to be attributed incorrectly to the irregular component instead of the trend-cycle. Although this misclassification does not alter the seasonally adjusted outcomes, selecting different outlier types can affect the extent of series revisions and may also influence the detection of turning points. ESS guidelines on seasonal adjustment, particularly in chapter 2.8 concerning the “Treatment of outliers at the end of the series and at the beginning of a major economic change,” recommend modeling outliers at the end of a time series based on statistical criteria and economic information, especially during periods of significant economic change. However, in the case of COVID-19, the situation is more complex. The outlier may appear in the trend-cycle component or the irregular component, depending on the final specification. Since the seasonally/calendar adjusted results include both components, the impact of the COVID-19 crisis on the data remains evident.

To address this issue, we followed Eurostat’s guidelines and initially modeled the crisis period (2020Q1) as an additive outlier. As new data became available, the type of outlier was re-evaluated, with the possibility of revising it to a transitory change or a level shift or maintaining it as an additive outlier. This decision was made based on a comparative analysis of the three options, starting with the successive periods. This methodological rigor ensured that the data’s integrity and the economic narrative remained consistent throughout the crisis period.

7. CONCLUSION

In this paper, we have analyzed the implications of transitioning from the X12-ARIMA to the X13-ARIMA-SEATS method for the seasonal adjustment of Armenia’s QNA series. The X13-ARIMA-SEATS method, which incorporates the SEATS filter and advanced diagnostics, provides a more robust and reliable approach to capturing nonlinear trends and structural breaks in time series data. The new framework also aligns with the ESS guidelines (2015) and IMF recommendations, which summarize best standards and practices regarding the various aspects of the seasonal adjustment process.

Our findings highlight the significant methodological advancements introduced by the new framework and its positive impact on the interpretation of key economic indicators. We have demonstrated that, although the indirect method may be more susceptible to revisions, it is preferable for Armenia given the divergent seasonal patterns among GDP components and the importance of preserving accounting relationships. Additionally, we highlight the advantages of the partial concurrent adjustment strategy, which balances accuracy with the minimization of revisions. Furthermore, our findings on the relationship between price, volume, and value indices

underscore the importance of deriving implicit price deflators as residuals from seasonally adjusted volume and current price data rather than directly adjusting them, as most QNA series are derived from nominal data.

To ensure the quality of the seasonal adjustment process, we conducted a comprehensive set of diagnostic tests to evaluate various aspects of the adjustment, including the absence of residual seasonality, the validity of underlying assumptions, and the stability of the results. The results of these tests indicate that, overall, the seasonally adjusted QNA series are free from residual seasonality, the pre-adjustment models meet all necessary assumptions, and the seasonal adjustment results are stable. We have also addressed the specific challenges posed by the COVID-19 crisis in the context of seasonal adjustment by carefully modeling the outlier associated with this event as additive outliers at the beginning of the crisis and then revisiting if necessary to ensure the data integrity and the economic narrative remain consistent throughout this period.

Appendix A. Codes of NACE Sectors

NACE Code	Economic Area
A	Agriculture, forestry, and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam, and air conditioning supply
E	Water supply, sewerage, waste management, and remediation activities
F	Construction
G	Wholesale and retail trade, repair of motor vehicles and motorcycles
H	Transportation and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific, and technical activities
N	Administrative and support service activities
O	Public administration and defense, compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment, and recreation
S	Other service activities
T	Activities of households as employers; undifferentiated goods and services producing activities of households for own use

Source: Statistical classification of economic activities in EU

(<https://ec.europa.eu/eurostat/web/nace>).

Appendix B. P-Values from Seasonality Tests for Indirectly Adjusted QNA Series

NACE Code	Autocorrelations at Seasonal Lags	Friedman	Kruskall-Wallis	Periodogram	Seasonal Dummies
A	0.656	0.896	0.647	0.729	0.710
B+C+D+E	0.834	0.766	0.631	0.669	0.603
F	0.194	0.819	0.761	0.691	0.802
G+H+I	0.117	0.664	0.431	0.612	0.647
J	0.815	0.997	0.865	0.803	0.633
K	0.973	0.241	0.316	0.315	0.331
L	1.000	0.921	0.997	0.915	0.871
M+N	0.900	0.965	0.868	0.922	0.977
O+P+Q	1.000	0.818	0.868	0.598	0.642
R+S+T	0.063	0.615	0.513	0.375	0.222

Source: Authors' calculations.

Appendix C. P-Values from Seasonality Tests for Implicit Price Deflators

NACE Code	Autocorrelations at Seasonal Lags	Friedman	Kruskall-Wallis	Periodogram	Seasonal Dummies
A	1.000	0.871	0.776	0.679	0.632
B	0.916	0.408	0.377	0.301	0.332
C	0.518	0.182	0.308	0.254	0.410
D	1.000	0.314	0.465	0.288	0.368
E	0.363	0.209	0.352	0.509	0.091
F	0.331	0.444	0.214	0.121	0.382
G	0.798	0.614	0.252	0.262	0.305
H	1.000	0.219	0.271	0.431	0.586
I	0.838	0.166	0.348	0.156	0.097
J	0.896	0.200	0.210	0.495	0.398
K	0.288	0.220	0.094	0.306	0.326
L	0.999	0.921	0.992	0.999	0.998
M	0.989	0.483	0.798	0.903	0.885
N	0.624	0.871	0.574	0.546	0.657
O	1.000	0.343	0.258	0.269	0.402
P	0.245	0.240	0.155	0.144	0.171
Q	0.443	0.714	0.135	0.083	0.074
R	1.000	0.663	0.768	0.954	0.953
S	1.000	0.663	0.909	0.889	0.968
T	0.419	0.664	0.809	0.960	0.948

Source: Authors' calculations.

Appendix D. Metadata

Time series	Expenditure and production components of GDP <ul style="list-style-type: none">- at current prices- chained volume indices (2012=100)
Frequency	Quarterly
Software	JDemetra+, v2.2.2
Method	X13-ARIMA-SEATS
Calendar used	National calendar with nonworking days defined by the law of RA “On Holidays and Memorial Days of the Republic of Armenia”, with Easter and leap year effects
Outlier detection and correction	Automatic, except in special situations (e.g., pandemic modeling)
Selection of model parameters and filters	Automatic
Method of decomposition	Additive, multiplicative
Direct/indirect adjustment	Indirect adjustment
Benchmarking with nonseasonally adjusted data	Yes
Current/concurrent adjustment	Partial concurrent adjustment where the model, filters, outliers, and calendar regressors are revised once a year, and seasonal and calendar factors are estimated every time new data becomes available
Quality indicators	Statistical tests and other tools offered by JDemetra+
Release calendar	On the 65th/67th day after the end of the reporting quarter
Revision of adjusted data	Seasonally adjusted data is revised starting from the 1st quarter of the 3rd year preceding the reporting year

Source: ARMSTAT (<https://armstat.am/en/?nid=202>).

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From Noise to Turning Points

A New Framework for Seasonal Adjustment in Armenia

This paper evaluates the transition to the X13-ARIMA-SEATS framework for the seasonal adjustment of Armenia's quarterly national accounts, highlighting its role in detecting economic turning points. The paper discusses best practices for seasonal adjustment and strategies for accurate real-time economic analysis.

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