ISSN 2789-3308

ECONOMIC REVIEW
National Bank of the Republic of Kazakhstan

No. 3, 2021

Nur-Sultan, 2021

ECONOMIC REVIEW
National Bank of the Republic of Kazakhstan

Published by: National Bank of the Republic of Kazakhstan

ISSN 2789-3308

ECONOMIC REVIEW

of the National Bank of the Republic of Kazakhstan

No. 3, 2021

CONTENTS

ASSESSING THE QUALITY OF LOAN PORTFOLIO BASED ON THE LOAN LEVEL DATA

Khakimzhanov S. T. – Head of the Research and Analysis Department of the National Bank of Kazakhstan

Konurbayeva N. A.– Chief Specialist-Analyst, Division of financial market's research, Research and Analysis Department of the National Bank of Kazakhstan

Nurkhanova O. V. – Head of Division of financial market's research, Research and Analysis Department of the National Bank of Kazakhstan

This Paper analyzes the source of information – the Credit Registry – to assess the portfolio of banks at the level of each loan (loan level data). The Paper introduces the concept of default based on indirect indicators using the Credit Registry. Indicators that can be used to assess the dynamics in the status of each loan with the ability to aggregate at the borrower level are being designed. An analytical assessment is conducted to identify refinanced loans and "evergreen" loans. The categories for the distribution of loans within the portfolio are described and introduced in order to identify the deterioration of loan on a timely basis, allowing the application of early response measures by the supervisor as well as the assessment of credit risk at the banking system's level. The quality of the methodology was checked on the basis of available historical information about the transfer of the portfolio to the Problem Loans Fund and the recognition by the bank of loans past due more than 90 days before the license was revoked; in addition, the volume of false positives detected by the methodology but subsequently submitted to the Credit Registry with zero main debt was assessed. The presented methodology is the first attempt of applying a loan-based analysis in Kazakhstan that can be developed using the new extended loan and borrower data incorporated into the Credit Registry since July 2019. Besides, the next stage after assessing the quality of portfolio will be the assessment of probability of borrower's default as well as the stress testing.

Key Words: credit risk, loan review, probability of default, Credit Registry, loan-level review, refinancing, "evergreen" loans.

JEL-Classification: C81, C83, G21.

1. Introduction

Creation of the Credit Registry was driven by the need of the regulator and the central bank for the data about the status of bank loans with a high degree of granularity, which would provide an opportunity for a more accurate assessment of the quality of loans, adequacy of provisions and, accordingly, for supervision of reliable maintenance of capital adequacy as the main prudential requirement.

The Credit Registry would allow the regulator to make its own judgment about the effectiveness of each individual bank loan based on the actual data and, therefore, on the financial condition of that bank.

The NBK's Credit Registry acquired its current format at the beginning of 2013, and some fields were additionally included in mid-2019. Some of the fields contain factual information and some of the fields – the judgment of a bank or an appraiser.

The initial analysis of the data in the Credit Registry showed that the servicing of their loans by borrowers, just like the loan accounting practices used by banks, do not fully correspond to the concepts of a standard performing loan. Therefore, the main objective of creating a Credit Registry was realized only partially. As a result, the main difficulty faced by the users of the Credit Registry was the interpretation of actual data in the Credit Registry in such a way so as to give an assessment of events that happened or were likely to occur in the life of the loan.

We tried to apply an approach using all the possibilities and overcoming the existing limitations in the data of the Credit Registry to assess the quality of banks' loan portfolio at the level of an individual loan. The problems we faced were primarily related to the data quality. They can be roughly divided into three reasons. First, poor discipline of filling out the data by banks. Second, there is a discrepancy in the data structure and the ideal data model for describing the loan life cycle. Third, the discrepancy between the objective assessment and the assessment of data provided by banks.

In this paper, we have focused on analyzing the loan level data; although from an economic point of view, it would be more informative to use assessment at the borrower level. Nevertheless, we found it necessary and practically useful in the first stage of data analysis to limit the scope of analysis to questions at the level of each individual loan. In general, any additional data on the loan, the borrower, the class of borrowers and the conditions in which the borrower operates, the borrower's counterparties, the borrower's accounts receivable will certainly significantly improve the assessment of the loan quality. Thus, the improvement of the designed method for analyzing the quality of loans by expanding the range of data can continue indefinitely. However, the primary task in the analysis is to improve the quality of data on an individual loan, including the data on servicing the terms and conditions of the agreement (repayment of the principal debt and accrued interest) and the data on events reflecting a change in the relationship between the borrower and the lender (refinancing, restructuring). This paper is devoted precisely to this initial stage of analysis.

2. Credit Registry in Kazakhstan

2.1 History of the Credit Registry Evolution

In the international practice, the collection of data on loans began at different times. For example, in Germany, the collection began in 1934. However, the data covered only those loans that exceeded the established threshold per borrower. Initially, the threshold was € 1.5 million; at present, the threshold has been lowered to € 1 million and work is underway to lower the threshold further [7]. The countries of Eastern Europe began to introduce state Credit Registrys much later: in Latvia – in 2008, in Romania – in 2012. In Latvia, there is no threshold for providing information, and in Romania, it is 4,500 US dollars in the national currency equivalent [8]. Regulators and central banks in various countries are working to lower or remove the threshold. At the moment, credit bureaus, both public and private, operate almost everywhere. At the same time, most countries have a state Credit Registry (Appendix, Table 1).

As is shown by the rate of public credit registry coverage calculated by the World Bank based on data from 264 countries of the world, coverage is growing from year to year and by 2019 it covered more than 15% of the adult population (against 8% in 2011).

The National Bank's Credit Registry began functioning and was used to collect indicators and data in 1996. Banks provided information on credit and contingent liabilities exceeding 5 million tenge, and/or if the borrower's debt on all loans provided to him/her exceeded 5 million tenge (71 thousand dollars) [9]. In 1998, the threshold for liabilities provided was lowered to 3 million tenge (about 36 thousand dollars at the exchange rate of that period). A condition was put in place that the data on small businesses is sent in full, and on individuals – from 1 million tenge.

In 2004, the limits on loan amounts were removed. From that moment on, information was provided on all loans and contingent liabilities, with the exception of guarantees issued for participation in the tender and guarantees secured by money. In 2012, the list of indicators that banks sent to the National Bank was extended.

For the initial collection of a limited number of data from 1996 to 2009, the "Credit Registry" AIS was used, which was updated from 2009 to 2013 into the upgraded "Credit Registry" AIS due to the addition of new indicators. Subsequently, the National Bank developed a concept paper for the transition to a data-centric approach. It involves the transfer of data at the indicator level through a single window and contributes to the improvement in the quality of the information provided. To achieve this goal, in 2013 an automatic information system "Unified Indicator Collection System" (UICS) was developed with 89 indicators. In July 2019, the system was revised and owing to the revision was supplemented with new indicators, whose number was brought to 189 . It is planned to improve this system by integrating it with the existing government databases, to reduce the data transmission load on banks and also to introduce an electronic folder system.

2.2 Credit Registry as the Source of Information

The data that allow for a qualitative analysis of the portfolio appeared in the Credit Registry since 01.04.2013, when the number of indicators was increased to 89. Banks provide data on loans, contingent liabilities and reverse repos on a monthly basis, it was agreed that the frequency of data provision will be increased. The data as at the first day of each month is used for the analysis.

Historically, the number of loans for which information is provided has been growing. The database contains data on 38.9 million unique loans that were provided during the period from 1992 to 2020. As at June 1, 2020, the number of loans exceeds 14.6 million (Table 2), where more loans to individuals account for over 90% (Table 3). However, in the structure of banks' portfolios in terms of the principal debt, loans from corporate entities prevail and the bulk of all credit operations is covered by loans and credit cards of banks (Table 4).

At present, the data for the Credit Registry is furnished by 33 organizations. These include 27 second-tier banks, the Development Bank of Kazakhstan, 2 mortgage organizations, and 3 subsidiaries operating in the sphere of agro-industrial complex. Historically, the maximum number of organizations was 48.

2.2.1. Shortcomings of the Credit Registry

As noted above, the main problem we faced when using the Credit Registry data was the quality of information provided by banks. Initially, banks were required to provide the full volume of all indicators on a monthly basis, whereas in fact, indicators for which information was not provided were often identified. For example, in the upgraded Credit Registry, which existed before April 2013, when analyzing the “Collateral value” indicator, a lack of information was revealed, and the users of the Credit Registry did not have an understanding of whether the collateral was sold or the bank simply did not provide information on the value of collateral. At the same time, banks can communicate information at its initial appearance or in case of its change. There are currently no empty values in the database but the accuracy of information is not guaranteed. Therefore, the quality of information is checked using logical controls and post-controls, which are constantly being updated and modified.

Initially, the names of organizations, the surnames and names of borrowers were provided in different spellings, which did not allow matching borrowers between banks. Mandatory provision of BIN and IIN reduced the risk of providing false information and made it possible to track the borrower within the banking system. However, in this case, too, it was necessary to prescribe control, since sometimes an incomplete IIN or BIN was provided. In the existing database, the risk of providing an unauthentic IIN or BIN is minimized. Also, a mechanism for constructing a universal borrower number was developed to compare borrowers. It is based on checking the identity of the BIN/IIN, the name of the organization and the TRN/SIC. As at June 1, 2020, the database contains information on 8 738 thousand bank borrowers.

To understand and better monitor the status of the portfolio, new indicators were added, which are included in the second phase of the UICS and began to be collected from July 1, 2019. This is how the flow indicators appeared: the amount of payments actually received, disbursed and repaid, the present value of future cash flows (expected value to be received) for heterogeneous loans. Also included are the indicators that allow assessing the stage of completion of the loan: these include refinancing, sale, assignment to organizations that manage distressed assets. Indicators that allow assessing the quality of the pledged property are: the date of collateral appraisal, the market value of collateral, the value of collateral on the bank's balance sheet, documents and the name of the appraiser, the basis for termination of collateral. The following indicators are also added: restructuring performance, a sign of the borrower’s impairment, repayment schedules, and an interest rate type: floating or fixed.

The new indicators will allow building models for assessing the level of loss given default (LGD). However, in order to build models based on a monthly data, a history of at least 5 years is required. Given that new indicators are collected only from the beginning of July 2019, the construction of informative models with them will be possible no earlier than the end of 2024.

For an even more extensive analysis, the Credit Registry requires that the accounting information in accordance with IFRS 9 and information about the borrower’s financial condition should be provided in addition. However, again, the possibility of in-depth analysis is limited by the banks’ discipline in filling out information, as well as by the need to accumulate history. Concurrently, the National Bank is working on accessing additional information from other government sources.

3. Estimates and Assumptions

3.1 Assessing the Discipline of Loan Servicing

The simplest indicator of the discipline of loan servicing is the timely payment in the amount sufficient for the principal debt to decrease after each payment. This indicator is the reduction in the principal debt for the given period. A derived figure from this indicator is a sequence over a longer period of time than one month, that is, a continuous sequence of indicators of reduction in the principal debt.

3.2 Estimating Cash Flows on the Loan

The data field, where the cash flow on the loan is shown, has existed in the current version of the Credit Registry since 2013; however, due to the low discipline of filling out this information, most of the exponents in this field are empty. The absence of such critical piece of information for assessing the condition of the loan forced us to use assumptions in estimating cash flows that reflect the standard practice of banks in calculating interest, choosing loan repayment schedules, as well as accounting requirements.

Our estimate of cash flows is based on the movement of the balance sheet items of the loan: the principal balance and the accrued interest. The assessment of the flow of principal debt repayment was made as the difference between the balances of the principal debt of two consecutive periods. The estimation of the flow directed to the repayment of the accrued interest was based on the assumption that the loan payments are allocated to the repayment of the principal and the interest in accordance with the principle of primary interest repayment in the amount not exceeding the repayment schedule. The remainder of the payment is used to pay off the principal debt.

This model assumes that each payment includes a non-zero principal repayment every period, just like the fact that the loan does not increase the principal debt, as, for example, in the cases of credit lines, which are an object of a higher hierarchy level in the data model. Credit lines are actually a framework agreement whereunder many individual loans can be concluded. Such examples may include negative amortization loans, loans with capitalization of overdue accrued interest during the period of restructuring of a non-performing loan.

A more difficult stage in the construction of the methodology is the assessment of cash flows aimed at the repayment of accrued interest. The law of motion for this balance sheet item is the addition of accrual for the current period and repayment of the previous period.

The second complication in the assessment was the requirements of international standards prohibiting the accrual of interest for loans that meet the criteria of non-performing loans. Therefore, to assess the fact of payment, that is, without taking into account its size and compliance with obligations according to the repayment schedule, we introduced an additional assumption. In particular, we assumed that any partial repayment or repayment in an amount exceeding the minimum required amount, first of all, is always used to repay the accrued interest in an amount not exceeding the volume according to the repayment schedule, and the remaining amount of payment is used to pay off the principal debt. Thus, the actual reduction in the principal debt is an indication that the payment in the previous period actually took place.

3.3 Default Definition

In the recommendations for defining default, international financial institutions generally recognize as non-performing loans such loans that are past due on the principal debt and/or interest 90 days or more. An additional criterion used in these recommendations is the client's unwillingness to pay and/or a significant deterioration in the financial condition of the borrower. Examples of definitions of default applied prior to the introduction of new standards are given in Table 5 of the Appendix.

In Kazakhstan, the definition of default usually means more than three months delay. This definition is not an arbitrary choice of the duration of delay – it is tied to the definition of past due used in the civil and business law. A past due of more than three months gives a lender the right to start claim work, declare a default, and consider the borrower as defaulting on the loan agreement. For a bank or lender interested in restoring the quality of the loan or in restoring the value, at least partially, recognition of the loan as overdue and, therefore, the timely initiation of a claim work is the most optimal course of action. Since the borrower also has information about the consequences of a past due of more than three months, violation of the terms of servicing a loan with a past due of more than 90 days is also informative for the borrower in terms of his/her ability and willingness to service a loan in the future. For this reason, the minimum overdue period is the dividing line between performing and non-performing loans.

However, if the consequences of past due of more than three months, due to certain reasons, do not have serious consequences for the borrower, then the information value of this cut-off point decreases. Such circumstances may arise, for example, when a bank is more concerned about the consequences of delinquency recognition for capital adequacy and the impact on its ability to comply with prudential requirements.

In such cases, the bank prefers to maintain the appearance of no losses in the event of an actual deterioration in the loan repayment, neglecting to take measures in order to restore the value of this loan. Alternatively, for example, when the borrower of the bank is a related person of the bank and can count on a softer attitude – forbearance instruments are applied to the loan. In all these cases, the deterioration in repayment on the border of three months cannot have grounds for being more significant than at the border of two months, and at the border of four months. In other words, the indicator of duration of the loan delinquency (less than 90 days or more than 90 days) is no longer informative. In such cases, the information value of a loan default already depends on what expectations the borrower has about the bank's actions in relation to him/her, depending on the duration of the past due.

For this reason, during the analysis and initial qualification of the loan status, it is advisable not to proceed from the assumption of the greatest information value of a three-month past due, but to assess the conditional probabilities of continuing deterioration in the quality of loan service for various periods of past due and to identify the boundaries and definitions depending on observations.

The initial analysis revealed a significant proportion of loans that banks do not recognize as non-performing, but which, according to service metrics obtained on the basis of the Credit Registry data, are in fact past due for more than three months. A significant share of such loans in the portfolio indicates that the recognition of all these loans as non-performing and, accordingly, the creation of provisions for them will lead to deterioration in the bank's capital adequacy and potentially to a violation of prudential ratios by such bank. Thus, there is at least one reason to assume the loss of information value of the standard definition of default, as well as the bank's desire to hide a large amount of non-performing loans in its portfolio.

4. Methodology for Assessing the Quality of Loan Portfolio

4.1 Loan Quality Indicators

Taking into account the described limitations in the available data of the Credit Registry, as well as the non-standard behavior of the bank in terms of loan accounting and the borrower's behavior in relation to servicing the loan, we have designed the indicators that allow interpreting the viability of the loan according to the following criteria:

- a monthly decline in the principal debt during consecutive months ($X_{1,t}$- NDB);

- significance of the amounts of accrued interest ($X_{2,t}$- AI);

- actual repayment/non-repayment of the loan ($X_{3,t}$).

Sign of a Non-Declining Balance, or NDB. The first indicator of a violation of the loan service discipline is the absence of a reduction in the principal debt, including the change in the rate of the loan. This indicator is an objective evidence of a non-performing asset with a low payback. Non-declining balance was calculated from the ratio of current value of principal debt to the previous one:

$$X_{1,t} = \frac{PD_t}{PD_{t-1}} - 1,$$

where PD is the principal debt on the loan

t – current period,

t-1 – previous reporting period.

In building this indicator at the level of one period, one must select a parameter: decline or sensitivity. A decline of 0.2% was chosen as the threshold of sensitivity, which roughly corresponds to a decrease in the rate of reduction of the principal debt for loans with an annuity repayment schedule, but mortgage loans with a term of more than 15 years are an exception.

If the value is $X_{1,t} \in [-0,2\%;0,2\%]$ or $X_{1,t} > 0,2\%$, then the loan has a non-declining principal debt, i.e. it has a sign of NDB. To create a complete picture of deterioration in the quality of a loan, we came up with a derived index that shows the number of NDB periods.

In order to calculate the number of NDB periods, a variable is introduced:

$$Y_t = \begin{cases} Y_{t-1} + 1, \text{if } X_{1,t} \geq -0,2\% \\ 0, \text{if } X_{1,t} < -0,2\% \end{cases}$$

The variable is reduced to zero if a payment on the loan is received, i.e. $X_{1,t} < -0.2\%$. If the condition is not met, then from period to period the variable is increased by one, which corresponds to the number of months of NDB on the loan.

Analyzing loans with different numbers of months of NDB and evaluating how many months of non-decline is problematic for a loan, based on the historical data of the Credit Registry the result was obtained that with NDB of ≥ 12 months, the loan will become bad with a 90% probability. Thus, the presence of the NDB sign for 12 consecutive months is the ground for classifying the loan as defaulted with the requirement for full coverage by collateral and/or provisions.

This approach is based on the assumption that the loans in question do not have the conditions for the possibility of the principal debt repayment at the end of the term or according to an individual schedule. However, the presence of a condition for the principal debt repayment at the end of the term implies large amounts of accrued interest, thus already posing risks for the borrower's solvency.

Accrued Interest to the Principal Debt. In the absence of interest repayment on the loan, amounts are accumulated in the accrued interest indicator. In this regard, the second indicator was reviewed – the ratio of the current value of the accrued interest on the loan to the principal debt (PD):

$$X_{2,t} = \frac{\mathrm{AI}_t}{\mathrm{PD}_t},$$

where AI is the interest accrued on the loan at time t.

The sign of the AI/PD ratio is used in conjunction with the sign of NDB on PD. In case of a monthly repayment, the accrued interest must be reduced to zero, otherwise it continues to accumulate. The threshold level for determining the significance of the accumulated interest in relation to the PD was adopted at the level of 5%. The choice of this threshold was driven by the presence of a prudential ratio whereunder the interest rate under the agreement should not exceed 60% per annum, which is 5% monthly.

The Balance of Accrued Interest and Estimated Accrual. The change in the balance of accrued interest and the estimated accrual, which is determined according to the terms of the agreement, provides an indicator for assessment of the information value of the AI indicator.

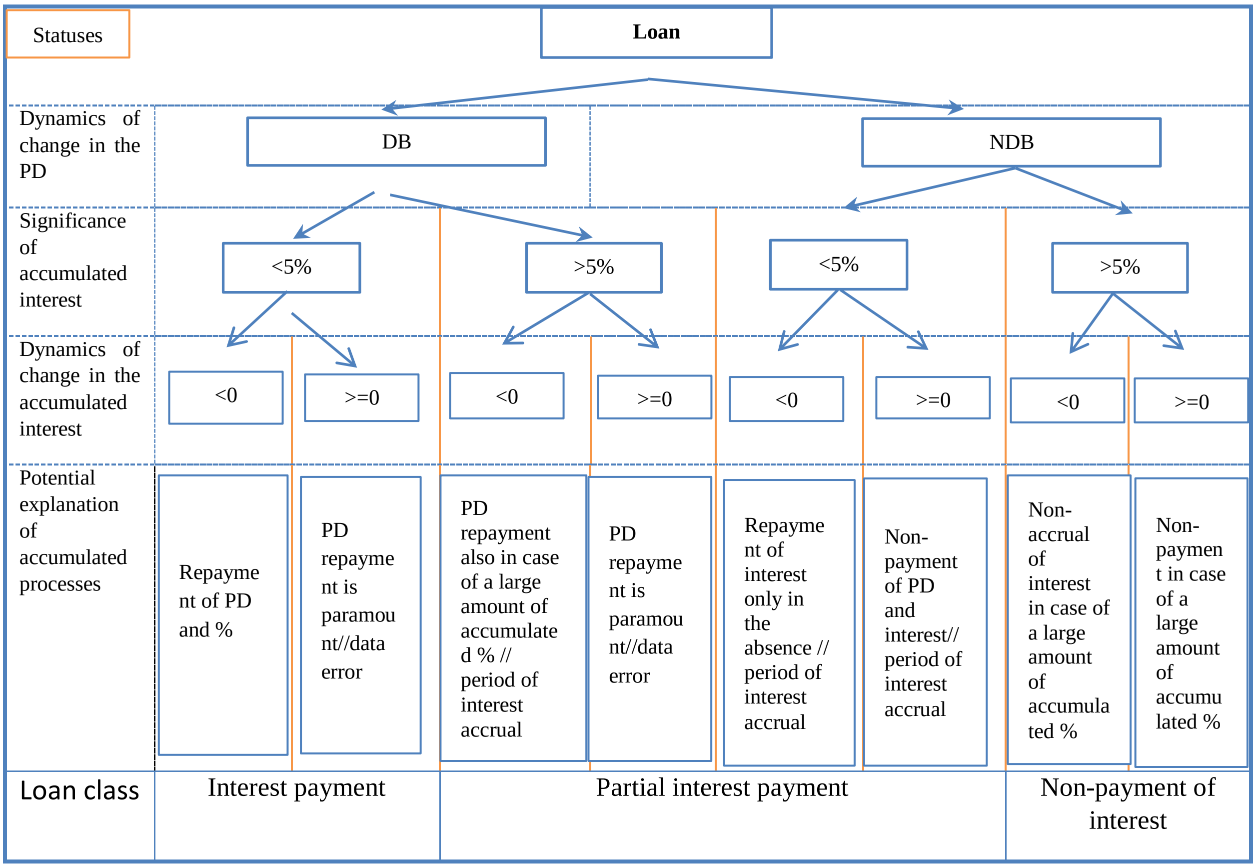
The relationship between the actual change in the balance of accrued interest for the month and the estimated change based on the interest rate and the term of the loan was considered as another indicator. It is an additional indication of the presence of interest repayment/suspension of interest accrual, or a sign of the absence of interest repayment.

$$X_{3,t} = \frac{\mathrm{AI}_t - \mathrm{AI}_{t-1}}{r/12 * \mathrm{PD}_t} - 1,,$$

where r – is an annual interest rate based on the terms of the agreement.

The threshold level for the indicator is taken at the level of -0.07. This feature is used in conjunction with the paragraph above, forming the feature of payment/partial payment/non-payment of interest. (Figure 1).

Figure 1. Classification of Portfolio Quality Indicators



Based on the above indicators, 6 loan quality statuses were created (in the order of deterioration): A, B, C, D+, D, F (non-performing loan).

Y_t	$X_{2,t}$ <5%		$X_{2,t}$ >=5%	
	$X_{3,t}$<0	$X_{3,t}$>=0	$X_{3,t}$<0	$X_{3,t}$>=0
0	A	data error	B	B

1-2	C	C	C	C
3 - 11	D+	data error	D	D
>=12	F	F	F	F

Further analysis showed that the ratio of the actual change in the accrued interest to the estimated one ($X_{3,t}$) does not add much information value since there was no data about the starting point and the number of days for calculating interest, therefore, the decision was made to exclude it. And the statuses were reclassified into the following:

Y_t	$X_{2,t}$ <5%	$X_{2,t}$ >=5%
0	A	B
1-2	C	C
3 - 11	D+	D
>=12	F	F

Based on the analysis of the data and the construction of intersections, we have given a new definition of default, which corresponds to category F in the table, that is, when the duration of the NDB is equal to or exceeds 12 times (months), the current date exceeds the repayment date under the agreement by 3 or more months, or if the loan was completely written off by the bank itself at time T. Additionally, status F includes loans with overdue debt over 90 days as recognized by the bank. Further in the paper, such loans are indicated as 90+ (bank's opinion).

Differentiation into categories allows tracking the gradual deterioration of the loan depending on the number of periods of non-decline of the principal debt and the accumulation of accrued interest. The categories are based on quantitative indicators, which are objective data and do not take into account the opinion of the bank. In addition, based on the data about the transition from other categories to the default category F, it is possible to estimate the probability of default taking into account historical data.

4.2 The Analytical Indicator of a Refinanced Loan

When, in order to maintain the level of capital adequacy, some banks prefer not to recognize loans as bad so as not to accrue additional provisions for them, and in cases where the borrower of the bank is its related person, such banks use forbearance instruments. One of these instruments is loan refinancing, which creates easing conditions for the loan and allows the bank to create a record with a new good history of such borrower.

If the bank decides to repay the borrower's loan by refinancing his/her old debt with a new loan, then the historical data (including the NDB indicator) on the previous loan ends at the time of refinancing. To exclude the possibility of improving the NDB indicator due to the loan refinancing, we created an analytical indicator that allows identifying the refinanced loans at the level of each borrower. The indicator is calculated as the ratio of the principal debt amount on new loans opened in the period t to the principal debt amount in the period t-1 of the loans closed in period t for the same borrower.

$$Ref_i = \frac{\sum_{j=1}^{k} \mathrm{PD}_{jit}}{\sum_{m=1}^{l} \mathrm{PD}_{mit-1}},$$

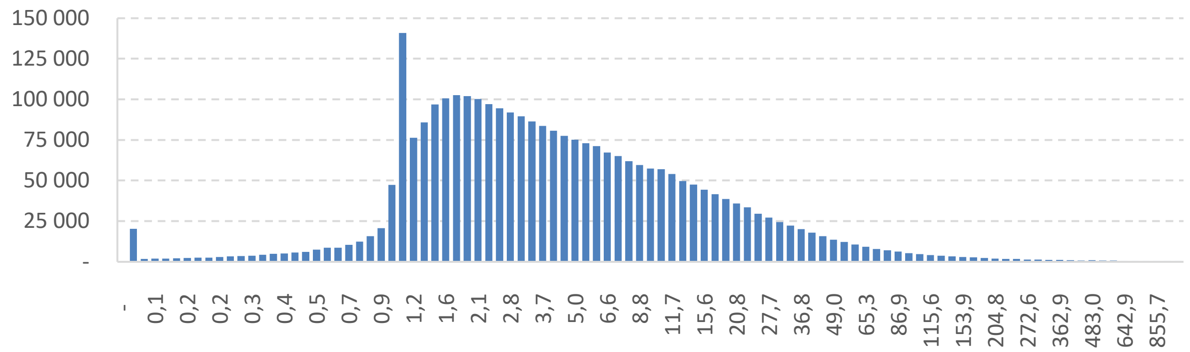
where i – borrower's identifier,

PD_{jit} – principal debt on new loans opened in the period t, of borrower i

PD_{mit-1} – principal debt on closed loans at the time t-1, of borrower i.

To analyze the refinancing, the sample was created from the data on loans and contingent liabilities provided to corporate entities and individuals and transferred to the Credit Registry from 01.04.2013 to 01.06.2018. The unit of calculation is a borrower who, in the same period, closes and opens one or more loans. The principal amount on closed loans is calculated for the previous period, the principal amount of opened loans is calculated for the current period, and their ratio is assessed. The calculated Ref_i ratios according to the above formula are shown in Figure 2.

Figure 2. Ref_i Distribution Calculated per Each Borrower

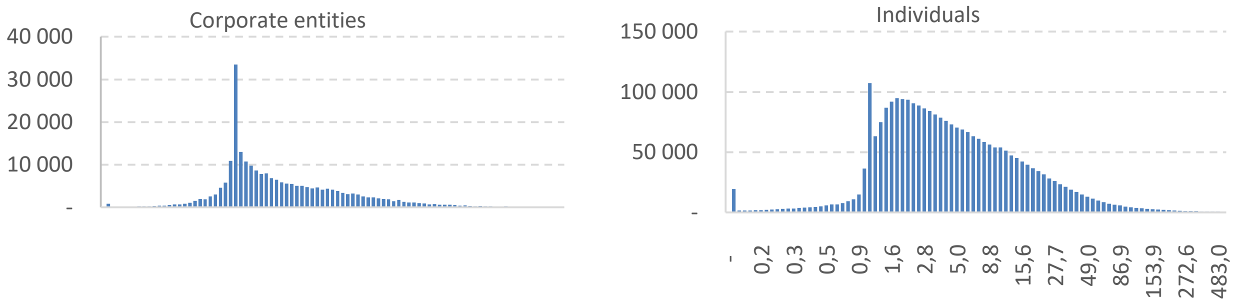


Source: NBK's Credit Registry

The figure shows that the largest number of loans falls on the ratio of about 1.1. To expand the sample, we decided that a loan can be regarded as refinanced if the value of the ratio belongs to the interval [0.8; 2]. In terms of the number of loans, about 30% fit this interval, and in terms of the principal debt amount – over 60%.

The Ref_i distribution by type of an entity is not the same (Figure 3). So, for corporate entities, the maximum number of borrowers falls on the ratio of 1.1 – over 33 thousand borrowers, the remaining values are much lower and do not exceed 13.5 thousand borrowers. Whereas for individuals, the maximum value also falls on 1.1 – over 107 thousand borrowers but about 90 to 95 thousand borrowers account for a ratio of 1.7 to 2.

Figure 3. Ref_i Distribution by the Type of an Entity



Source: NBK's Credit Registry

The number of unique borrowers among corporate entities in the specified period is 96,630, and among individuals – 7,403,621. The number of unique borrowers for whom the Refi ratio was calculated among corporate entities makes up 16,210, and among individuals – 530,942. However, during the reviewed period, one borrower could have its loans closed and opened several times, and, accordingly, each of them has its own Refi ratio. The number of Refi for corporate entities in the sample is 245,528, and for individuals – 2,680,421.

To assess the real status of new loans (refinanced loans), we continued to accumulate NDB periods, taking into account historical values. When several loans were closed at the same time, the maximum value of the NDB periods selected from the values for closed loans was taken to calculate the number of NDB periods. If several loans were opened for this borrower, then all new loans were assigned the maximum value of NDB periods. Thus, reclassification of the loan is conducted, which takes into account the entire history of the old loan (before the refinancing).

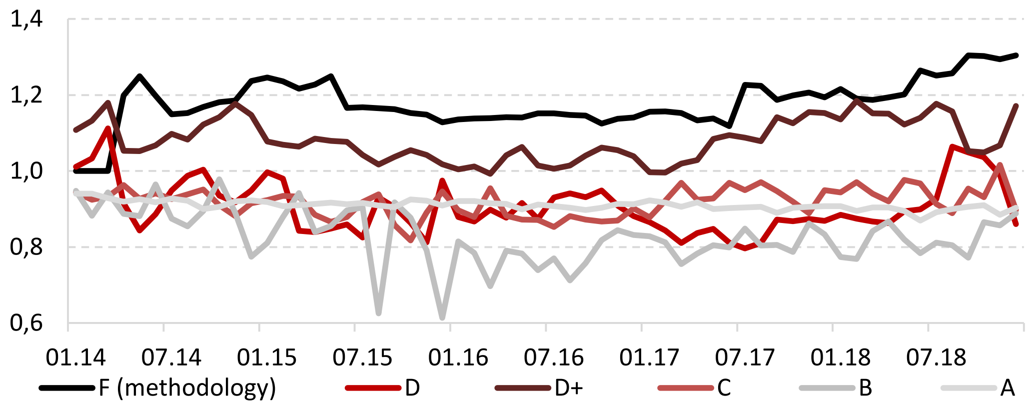
Without the use of the analytical refinancing indicator, the newly opened loan would look like a performing one and, in our estimation, would belong to category A, whereas if the new indicator is used its category may be worse. Figure 4 illustrates these intra-category loan movements when the refinancing ratio is applied to them.

If the borrower continues not to pay for a new loan, his category will shift to the worse if the analytical refinancing indicator is not applied. If we apply the refinancing indicator, then the NDB sign continues to accumulate.

If the refinancing indicator is applied, loans are in category D until 12 NDB periods are accumulated. Category D + includes loans that had 1 or 2 months of NDB before refinancing, and then the borrower did not pay PD, but repaid the interest

Classification by groups was conducted based on the analytical refinancing indicator. The

Figure 4. Categories with Refinancing/Categories without the Use of Refinancing Indicator

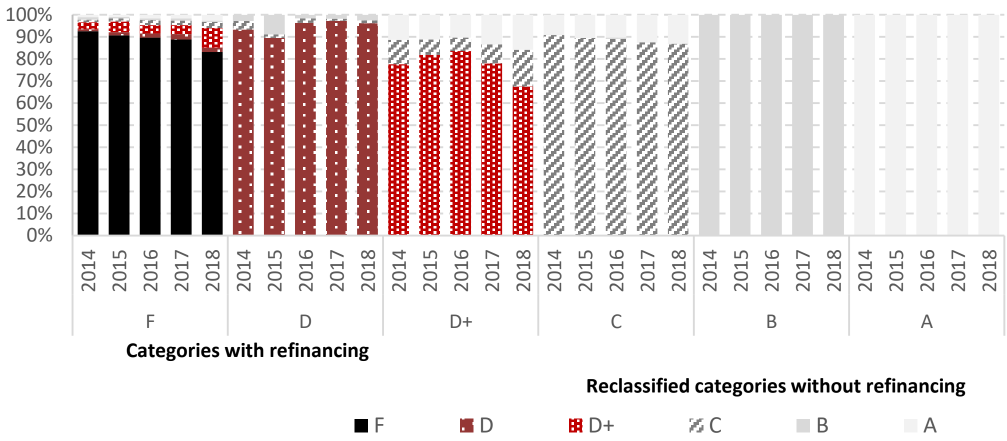


Source: NBK's Credit Registry

stage of the new loan was determined based on the number of NDB periods that the closed loans had. However, if there was a decrease in the level of principal debt for 12 consecutive months, the quality of the refinanced loan was recognized as improved according to the recommendations of the Basel Committee [1] and the regulator of European banks [2]. At the same time, the quality of portfolio using the refinancing indicator in the banking system is worse than without using it (Figure 5).

As can be seen from the Figures, the default category F according to our method is significantly higher than the bank indicates in its reports. So, for example, at the end of 2018, according to the banks' statements, loans 90+ (the bank's opinion) accounted for 7.5% of the portfolio, while category F (the methodology) without the use of the refinancing indicator included 15% of the portfolio, and with the use of the refinancing indicator – 19.6%. Thus, based on the group of indicators developed in the methodology, it is possible to assess the quality of portfolio and apply both in the supervisory practice and in assessment of the system's financial stability as well as to identify loans that require detailed analysis by both the off-site supervision and inspection oversight.

Figure 5. The Change in the Loan Category after the Use of the Refinancing Indicator



Source: NBK's Credit Registry

Additionally, other types can be used as categories, which are also calculated on the basis of periods of consecutive non-decline of the balance and the analytical refinancing indicator.

4.3 Methodology Validation

Assessing Type 1 Error

The quality control of the methodology was carried out on the basis of available information in the Credit Registry using historical data. In 2017 and 2018, Kazakh banks cleaned up their portfolio by assigning potentially impaired claims to the "Problem Loans Fund" JSC (the PLF) that was established to develop the market for distressed assets and is managed by the government. In addition, some banks, prior to revocation of their licenses, recognized a large volume of their loan portfolio as troubled portfolio i.e. classified it as loans past due 90 days or more. Based on the dates on which the assignment of claims took place and loans were recognized as past due over 90 days, the unloading from the Credit Registry was generated. The data as at June 1, 2017 were used as the date of recognition of the maximum amount of principal debt past due over 90 days. The data provided as at 01.01.2018, 01.10.2018 and 01.02.2019 were used as the date for assessing the transfer to the PLF.

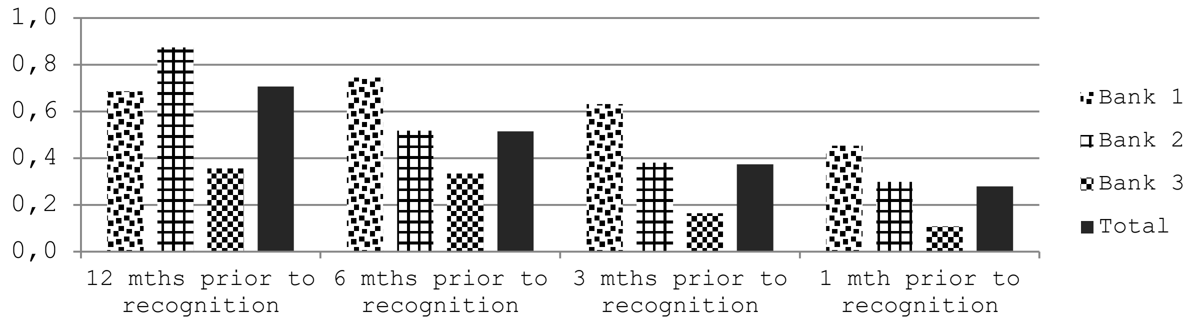
The first unloading to determine the volume of identified problem loans was made using the data on banks that recognized problem loans as well as transferred problem loans to the PLF. For this purpose, loans that banks recognized as troubled at certain dates were identified as well as those loans that were canceled (repaid) in the Credit Registry at the time of assignment of claims to the PLF. The second unloading was made using the assessment of those loans that were recognized by the methodology as troubled loans but at some point were repaid by clients. To do this, we used the data on loans from banks that meet capital adequacy ratios after applying a quality review of their portfolios according to our methodology. Using our indicators for assessing the quality of portfolio, a new level of non-performing loans and the required level of provisions were calculated. An assumption was made that provisions are created from the bank's profit for the corresponding period and accordingly reduced the capital level. The capital adequacy ratio was calculated based on the new capital. Banks that did not violate capital ratios, taking into account the original adjustments, were included in the second sample. The number of banks in the first and in the second case is the same.

In order to determine the percentage of loans identified under the methodology, the following sums of principal debt were used:

- a principal debt amount on loans recognized as non-performing (past due more than 90 days, the bank's opinion (90+)) and transferred loans – the amount repaid on the date of recognition;
- an amount of principal debt on the portfolio at a certain date – total principal debt for a certain period before the recognition of loans as troubled or transferred to the PLF.

As the time interval for the metrics, we used the periods before the bank recognized loans as troubled or transferred to the PLF: 1 month, 3 months, 6 months and 1 year before the corresponding dates indicated above. Figure 6 shows the shares of category F and 90+ of the principal debt amount of loans that were recognized by the bank as 90+ or were transferred with a value of 0 at the time of the portfolio assignment to the PLF.

Figure 6. Shares of Loans Not Recognized by the Methodology as Defaulted among Loans "Objectively Recognized" as Non-Performing



Source: NBK's Credit Registry

To exclude repayment in the current periods of standard performing loans according to the schedule, we adjusted it by the median of repayments, which was calculated for the previous 6 months using the analytical refinancing indicator. The largest value falls on 1 month before the recognition by the bank, but given that 12 months of the NDB of the principal debt on a loan are recognized as default, once can say that, based on the categories preceding the default, the methodology enables to identify loans that need to be focused on when assessing the bank's credit risk, in advance, since other categories are determined by a smaller number of months of NDB.

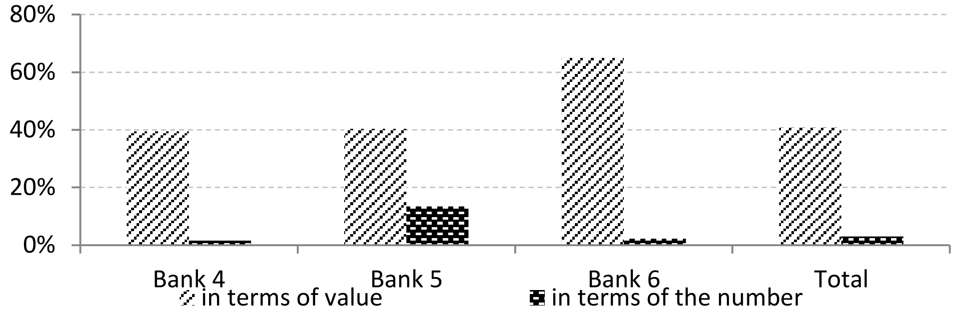
As can be seen from the figure, before the write-off or assignment of the claim to the PLF, banks recognized only 1.6% of the total amount of problem debt as troubled loans (90+). According to our estimates, in 1 month before the date of recognition, 72% of loans were troubled loans, and in 1 year before the date of recognition - about 30%. Therefore, the indicators used in the methodology help identify troubled loans not basing on the bank's opinion and in a larger volume.

Assessing Type 2 Error

However, type I error in our methodology is relatively big (30-40%), but it is by two orders less than in the banks' records (98%). The inclusion of categories D and C in the diagnostics, with an appropriate probability of non-repayment, can reduce type I error (Figure 7). However, it is also possible that the loans, which were classified by us as Type II diagnostic error in this calculation are not actually a diagnostic error. These loans were categorized as F, and after some time the debt balance on them was reduced to zero. The balance can be reduced to zero not only as a result of repayment of the loan by the borrower, but also as a result of its sale to the ODAM (Organization for Doubtful and Bad Assets Management). Since the ODAM is a related company, the sale can be made at a nominal, that is, inflated price. Such sale does not in any way affect the economic adequacy of capital on a consolidated basis, since it does not change the prospects for repayment on the part of the borrower; however, since banks in Kazakhstan are not regulated on a consolidated basis, the bank's losses on non-performing and bad loans can be hidden by selling it to the ODAM's balance sheet.

Therefore, our estimate of the type 2 error can be significantly exceeded. At present, we do not have the capacity to separate loans sold to the ODAM, since the loans sold to the ODAM are disappearing from the visibility of the Credit Registry. We do not see a possibility to solve the analytical problem of assessing the type 2 error without transiting to regulation on a consolidated basis or the obligatory transfer of reports to the Credit Registry from the ODAM.

Figure 7. Loans Classified as Defaulted a Month before Repayment
The Share of Loans that Have Ever Been Classified as Category F among Repaid Loans



Source: NBK's Credit Registry

Additionally, an analysis was carried out in respect of loans that were recognized as defaulted but were repaid by the borrowers on their own. The evidence of transfer to the Credit Registry with zero on the principal debt and the absence of write-off was recognized as repayment. As described above, the banks that have a sufficient level of capital were selected for the analysis, after the portfolio assessment on the basis of the methodology.

The sample consists of loans of three well-capitalized banks that have been repaid and had Category F during the life of a loan. The number of loans meeting these criteria was 235 800 with a face value of 1 161 billion tenge.

In their loan portfolio, loans that are classified as default F (under the methodology) are sorted out. The date when the loan was removed from the Credit Registry was taken as the repayment date. Loans written off by the bank to off-balance sheet accounts or loans with a partial principal and/or interest write-off were excluded from the sample. The share of loans was calculated by the number of loans that had category F but were repaid. The total number of such loans in the sample was 235,821. The category of false positive loans, as can be seen from the figure, mainly consists of loans classified by the bank as past due more than 90 days (90+ (the bank's opinion)) - 55% a month before closing.

The type II error, false positive detection of default, amounted to 3% of the number of repaid loans and 41% of the face value. This means that among small loans, type 2 error is insignificant. Almost the entire error in terms of volume occurs due to large loans.

A big mistake among large loans can be explained by the transfer to the ODAM; loans to state-owned companies (among the 15 largest loans (20% of the volume of each bank), 5 were provided to state-owned companies, or 45% of the volume); relatedness (realization of risk in case of loss of a shareholder's share in the capital); project financing (high risk) and non-standard repayment schedule.

Identifying default on large loans requires consideration of information about the borrower, its relationship with the bank (ODAM), the repayment schedule, and a lot of other data. Lack of this information overestimates Type 2 error for large loans.

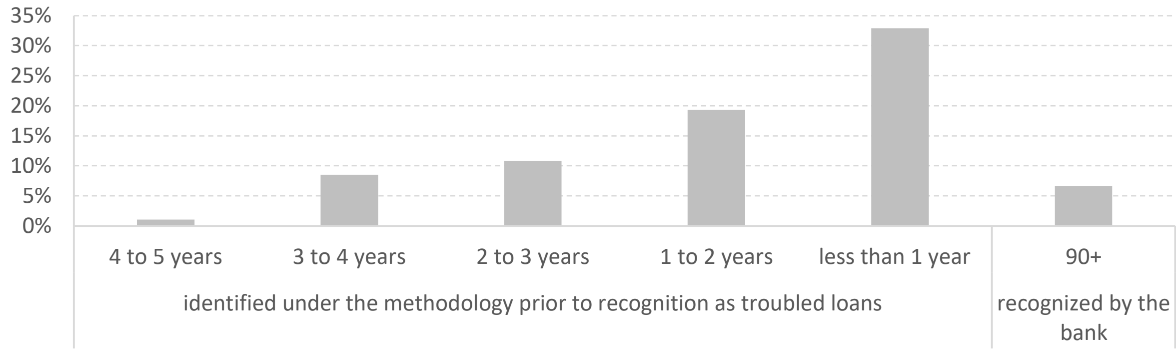
Estimating the Prediction Horizon

In order to estimate the prediction horizon for troubled loans, the sample similar to the first analysis was used.

For each loan, the date was set at the time of its recognition as defaulted and the value was calculated before the date of the claim assignment to the PLF and/or before the date of recognition of default by the bank. At the same time, for loans that had their status changed from default towards improvement and vice versa, the value of the first default was taken as the date according to the methodology.

Based on the analysis and using the methodology, about 20% of loans can be identified 1-2 years before the transition to default and over 30% during the year before default (Figure 8).

Figure 8. Time Frames for Identification of Defaulted Loans



Source: NBK's Credit Registry

Consequently, based on the methodology, it is possible to identify in advance the range of loans for which supervisory oversight is required. So, 1 year before problems arise, almost a third of troubled loans can be identified.

5. Scope

Our methodology enables to assess the quality of a bank's portfolio both at the level of each bank and at the system level. It allows dividing the portfolio into a performing portfolio on which the bank receives cash flows and a non-performing portfolio with no receipts of funds, not basing on the bank's judgments. In the future, it can be used for supervisory purposes and in assessing systemic risk at the level of the banking system.

For supervisory purposes, based on the methodology, it is possible to identify loans with no cash flows on an off-site basis and request information on them, use it in the portfolio valuation and calibrate the valuation using the SREP method, and then apply such data in supervisory judgment. In addition, the methodology can be applied in the process of inspections at the bank in order to formulate an independent objective judgment regarding the volume of troubled loans, and then check the credit files of these loans, borrowers and collateral.

As part of the systemic risk assessment at the banking system's level, the developed methodology enables to analyze the overall level of non-performing loans and potential losses when creating additional provisions, which will subsequently be attributed to the capital of banks. After dividing the portfolio into performing and non-performing portions, it is possible to estimate the amount of potential losses in case of changes in macroeconomic conditions affecting the quality of the performing portfolio by conducting the stress testing. Using the stages of loans described above, it is possible to construct a transition matrix from each stage for the corresponding class of loans and to determine the probability of transition to the stage of default. For non-performing loans, a 100% probability of default is assumed and the required level of provisions is estimated with a further revaluation of the capital level.

6. Conclusions and Further Research

Application of the developed methodology will enable to analyze the quality of bank loan portfolios not based on their subjective opinion, and to identify doubtful and defaulted loans in advance. However, there are certain restrictions associated with the fact that until mid-2019 there is no information on repayment schedules. Keeping track of repayment schedules is the area for expanding the methodology and conducting further research.

The current methodology prioritizes monthly loan repayments, and individual schedules are not taken into account. At the same time, an individual schedule may assume the repayment of most of the PD at the end of the term, which, in the absence of objective evidence of a high probability of debt repayment, may indicate a high risk and justify the application of a unified approach. Criteria are also required for classifying a loan as an investment one, taking into account the assessment of risks and feasibility, including the terms of the loan and legal aspects. For example, the condition for the provision of tranches, the order of the bank's priority to receive (expected) cash flows of the debtor, to collateral, etc.

The next step in using the methodology is to assess the probability of borrower's default by using the concept of default described above, as well as to build matrices for the transition from each category to the category of default and assess the necessary provisions for the corresponding loans.

In addition, after dividing the portfolio into a default and non-default one, it is planned to conduct the stress testing with a forecasting horizon of 1 year or more. In this case, the forecast will be built only for the performing portfolio, and the level of required provisions will be calculated for the estimated default portfolio. These efforts are areas of studies that are intended to be carried out in the coming years.

List of References

1. The Bank of International Settlements (BIS), Guidelines Prudential treatment of problem assets – definitions of non-performing exposures and forbearance, 2016 (https://www.bis.org/bcbs/publ/d403.pdf)

2. European Banking Authority (EBA), Guidelines on management of non-performing and forborne exposures, 2018, (https://www.eba.europa.eu/sites/default/documents/files/documents/10180/2425705/371ff4ba-d7db-4fa9-a3c7-231cb9c2a26a/Final%20Guidelines%20on%20management%20of%20non-performing%20and%20forborne%20exposures.pdf)

3. Hulster, Katia; Salomao-Garcia, Valeria, Loan classification and provisioning: Current practices in 26 countries, Financial sector advisory center, World Bank Group, 2016 (openknowledge.worldbank.org/handle/10986/21109)

4. National Bank of the Republic of Kazakhstan, Resolution of the Board of the National Bank of the Republic of Kazakhstan No. 170 "On Setting Regulatory Values and Calculation Methods for Prudential Ratios and Other Mandatory Ratios and Limits, the Amount of Bank Equity and the Rules for Calculation and FX Exposure Limits", September 2017 (as amended at 21.09.2020)

5. National Bank of the Republic of Kazakhstan, Resolution of the Board of the National Bank of the Republic of Kazakhstan No. 269 "On Approval of the Rules for Creation of Provisions (Reserves) in Accordance with International Financial Reporting Standards and Requirements of the Laws of the Republic of Kazakhstan on Accounting and Financial Reporting", December 2017 (as amended at 18.06.2020)

6. BIS, IFC Bulletin No 39 Indicators to Support Monetary and Financial Stability Analysis: Data Sources and Statistical Methodologies, April 2015 (https://www.bis.org/ifc/publ/ifcb39.pdf)

7. Michael Ritter, The German Central Credit Registry, International Finance Corporation, June 2017 (www.ifc.org/wps/wcm/connect/293d1635-0439-4007-af5a-efdd852f6bba/session_2_michael_ritter_bundesbank_heure_10h00.pdf?MOD=AJPERES&CVID=lNSU94r)

8. Dylnov D.V., Credit Bureaus. International Experience, Moscow, 2002 (https://iq.hse.ru/news/177844930.html)

9. National Bank of the Republic of Kazakhstan, Development of the Credit Registry in the National Bank of the Republic of Kazakhstan, June 2018

(www.eurasiancommission.org/ru/act/integr_i_makroec/dep_stat/info/Documents/Presentations_05-07-06-2018/12_KZ_Развитие кредитного регистра в НБРК.pptx)

10. Central Bank of Russia, Regulation on the Procedure for Creation of Reserves for Potential Loan Losses, Loan Debt and Debt Treated as Loan Debt by Credit Organizations, 12.06.2017

11. Turks & Caicos Islands Financial Services Commission, Statement of Guidance: Loan Classification and Provisioning, 2019 (tcifsc.tc/wp-content/uploads/2019/03/Statement-of-Guidance-Loan-Classification-and-Provisioning.pdf)

12. Donnery, Sharon & Fitzpatrick, Trevor & Greaney, Darren & McCann, Fergal & O'Keeffe, Micheal, "Resolving Non-Performing Loans in Ireland: 2010-2018," Quarterly Bulletin Articles, Central Bank of Ireland, 2018. (ideas.repec.org/a/cbi/qtbart/y2018m04p54-70.html)

13. National Bank of the Republic of Belarus, Resolution of the Board of the National Bank of the Republic of Belarus “On Approval of the Instruction on the Procedure for Creation and Use of Special Reserves for Potential Losses on Assets and Operations not Reported on the Balance Sheet” dated 28.09.2006, as amended at 03.03.2020 (http://www.nbrb.by/legislation/documents/pp138.pdf)

14. Avetisyan, Sergey, Regional-Specific Determinants of Non-Performing Loans, Central Bank of Armenia, June 4, 2019 (https://ssrn.com/abstract=3398897)

15. Deutsche BundesBank, Methodological notes, Financial Soundness Indicators, (https://www.bundesbank.de/en/statistics/sets-of-indicators/financial-soundness-indicators/methodological-notes-795772)

16. Andrii Chornous, Kateryna Lazarchuk, Legal Practicalities of Ukrainian Non-Performing Loans: Recent Changes and Perspectives, Hillmont Partners, 01.07.2020 (eba.com.ua/en/pravovi-aspekty-nepratsyuyuchyh-kredytiv-v-ukrayini-ostanni-zminy-ta-perspektyvy/)

17. Central Bank of Ireland, What is the Central Credit Registry? (www.centralbank.ie/consumer-hub/explainers/what-is-central-credit-register)

18. Юрченкова Т. А. Переход к сбору микроданных, май 2016 г, Дилижан (http://www.eurasiancommission.org/ru/act/integr_i_makroec/dep_stat/info/Documents/Presentation_31.06.2016/)

19. National Bank of the Republic of Belarus, Credit Registry – General Information, (www.nbrb.by/today/creditregistry)

20. the Latvijas Banka's, On the Credit Registry (www.bank.lv/en/tasks/credit-register/about-credit-register)

21. Liana Kirakosyan, The Central Bank of Armenia’s project of a credit registry, IFC Bulletin No 37,BIS, January 2014 (www.bis.org/ifc/publ/ifcb37c.pdf)

22. National Bank of Romania, Central Credit Registry Overview (www.bnro.ro/Central-Credit-Register-2786-Mobile.aspx)

23. The Bank of Slovenia, Central Credit Registry, (www.bsi.si/en/financial-stability/central-credit-register)

24. Grigorenko Yuri, Credit Registry of the National Bank of Ukraine: Bank Debtors Ought to be Scared, 23.03.2018 (https://112ua.tv/statji/kreditnyy-reestr-nbu-bankovskim-dolzhnikam-prikazano-boyatsya-438699.html)

25. European Central Bank, AnaCredit Q&A, (www.ecb.europa.eu/stats/money_credit_banking/anacredit/questions/html/index.en.html)

Appendix

Table 1. Examples of Countries with the State Credit Registry

Countries	Date of Establishment	State Credit Registry	Minimum Amount
Ireland [17]	2013	+	500 €
Russia ‘[18]	2015	+	0 Corporate entities only
Belarus [19]	2007	+	0
Latvia [20]	2008	+	0
Armenia [21]	2003	+	0
Germany [7]	1934	+	1mln. €
Romania [22]	2012	+	4500$
Slovenia [23]	2014	+	0
Ukraine [24]	2018	+	1500 €
AnaCredit ECB [25]	2018		25000€
Kazakhstan	2009	+	0

Source: Internet resources

Table 2. The Number of Loans Transferred by Organizations (thousands)
At the beginning of the period

Organization Type	Liability Types	2Q2013	2014	2015	2016	2017	2018	2019	2019	2019	2020	2H of 2020
Banks	active	4 675	6 001	6 787	7 061	7 408	8 869	10 648	11 138	9 320	10 198	9 397
	contingent	535	856	1 452	2 644	2 180	896	976	1 042	3 314	4 075	5 120
Other organizations	active	32	46	51	54	64	76	81	41	118	162	33
	contingent	9	14	23	33	25	51	56	0	35	20	121
Total		**5 251**	**6 916**	**8 314**	**9 792**	**9 676**	**9 893**	**11 761**	**12 221**	**12 788**	**14 455**	**14 670**

Source: NBK’s Credit Registry

Table 3. The Number of Loans Provided to Borrowers, by Entity Type

Organization Type	Entity Type	Apr. 2013	Jan. 2014	Jan. 2015	Jan. 2016	Jan. 2017	Jan. 2018	Jan. 2019	Jun. 2019	Jul. 2019	Jan. 2020	Jun. 2020
Banks	Banks/non-bank organizations	34	59	201	196	90	64	39	32	0	0	0
	Individual	5.04 mln.	6.6 mln.	7.86 mln.	9.3 mln.	9.14 mln.	9.57 mln.	11.43 mln.	11.96 mln.	12.12 mln.	13.54 mln.	13.6 mln.
	Corporate entity	169 919	260 835	380 934	407 150	446 061	195 667	197 720	222 672	513 156	734 114	911 553
Other organizations	Individual	35 869	53 693	66 246	53 077	46 977	50 811	499 17	40 728	109 203	134 204	105 655
	Corporate entity	4 752	5 829	7 866	33 961	41 643	76 761	86 564	175	44 542	48 102	48 219
Total		5.25 mln.	6.92 mln.	8.31 mln.	9.79 mln.	9.68 mln.	9.89 mln.	11.76 mln.	12.22 mln.	12.79 mln.	14.46 mln.	14.67 mln.

Source: NBK's Credit Registry

Table 4. Types of Loan Operations reported to the Credit Registry by Banks

Type of operation	Apr. 2013	Jan. 2014	Jan. 2015	Jan. 2016	Jan. 2017	Jan. 2018	Jan. 2019	Jun. 2019	Jul. 2019	Jan. 2020	Jun. 2020
loans	2 704 074	3 448 910	3 640 367	3 482 862	3 354 310	3 915 994	4 617 420	4 653 289	5 232 662	5 152 856	4 585 610
loans under trust	181	174	22 423	14 516	9 246	9 362	12 584	24 044	16 082	242 670	31 193
investment loan	276	424	454	42	38	174	157	46	49	52	52
working capital loan	6 484	3 958	4 265	3 091	2 481	1 846	1 428	1 119	420	542	471
credit card	1 927 237	2 514 992	3 075 661	3 531 023	3 996 309	4 847 095	6 068 341	6 469 731	4 160 405	4 868 652	4 776 100
credit line	2	4	0	0	0	1 260	1 076	697	467	39	17
Overdraft	67 974	76 797	93 655	80 899	99 864	153 430	9 981	10 122	8 757	7 952	3 266
Overnight	1	1	1	0	2	0	1	11	1	0	0
Repo operations	91	288	288	248	532	1 557	337	398	432	869	1 633
Factoring	80	60	53	64	28	850	114	1 282	937	1 554	867
Financial leasing	584	639	685	2 614	8 565	14 033	17 581	17 905	18 192	36 800	18 667
Forfeiting	56	68	0	0	0	0	0	0	0	10	11
Islamic instruments	59	49	54	68	53	80	121	165	174	254	287

Other asset types	6	28	11	1	2	1	0	0	6	48 407	11 039
Contingent liabilities	543 756	869 405	1 475 727	2 676 980	2 204 958	947 210	1 031 730	1 042 517	3 349 707	4 094 780	5 240 721

Source: NBK's Credit Registry

Table 5. The NPL Definition by Countries

Country	**Definition of a Non-Performing Loan**
Russia [10]	**Individual loans:** *minor deterioration of the borrower's financial condition* • + 5 days of past due on corporate loans / 30 days of past due on retail loans; *moderate deterioration of the borrower's financial condition* • + 30 days of past due on corporate loans / 60 days of past due on retail loans. **Homogenous loans:** • Over 90 days of past due on secured loans, • Over 30 days of past due on unsecured loans
Turkey [11]	**Doubtful loans**: - Loans past due at least 180 days, if they are not fully secured. - Debt recovery in full, which is very doubtful or unlikely. - The possibility of loss, but there are some factors that may improve the situation . - Permanent overdraft in excess of the limit, minimum activity across the account and collateral are not sufficient to cover the overdue debt. **Non-performing loans (loss):** - Loans are considered as bad. - Loans past due at least 365 days, if they are not fully secured. - Loans that can have some recurrent value but it is not practicable and not desirable to postpone their writing-off.
European Banking Authority (EBA) [2] Used for standardization of reporting in the European Union member countries	**Non-performing loans**: - 90-days past due (significant risk) - It is unlikely that the debt will be repaid in full without the sale of collateral (irrespective of any overdue amount or the number of days past due) - Impaired or allowed to default in accordance with the applicable accounting or regulatory framework. In respect of an individual borrower or debtor, all of its debt is recognized as non-performing if here is debt past due more than 90 days and its amount is > 20% of the borrower's total debt

Czech Republic[1] [3]	**Doubtful loans** Loans past due from 180 to 360 days **Non-performing loans (loss)** Loans past due more than 360 days
Ireland [12]	**Non-performing loans**: Loans past due more than 90 days The debtor is assessed as "unlikely to pay" in full without the sale of collateral on the loan.
Romania[2] [3]	**Non-performing loans**: The combination of past due days and the assessment of creditworthiness that should be conducted by the financial institution is used. All loans past due more than 90 days. The bankruptcy or any other financial reorganization of the borrower is taken into account
Belarus [13]	**Interbank loans** - past due over 31 days or more **Corporate loans** - unsecured with the signs of financial unsoundness past due from 8 days and more -unsecured from 31 days and more - secured from 91 days and more **Retail loans:** - past due from 91 days and more **Microcredits:** - past due from 91 days and more In classifying a loan, banks may use their own judgment but only towards the increase in credit risk
Latvia[2] [3]	**Doubtful loans** Loans past due from 91 to 180 days **Non-performing loans (loss)** Loans past due from 181 days or more
Armenia [14]	**Non-performing loans:** - full or partial repayment of the principal or interest is past due 90 days or more, or - interest payment for 90 days or more is capitalized (added to the amount of unpaid loan), or the repayment terms are adjusted (refinanced)) or is transferred to the amount of a new loan.

[1] From the first quarter of 2018, definitions recommended by the EBA are used
[2] At present, the definitions recommended by EBA are used

Germany [15]	**Non-performing loans**: - 90-days past due (significant risk) - It is unlikely that the debt will be repaid in full without the sale of collateral (irrespective of any overdue amount or the number of days past due)[3]
Slovenia[2] [3]	**Doubtful loans** Loans past due from 91 to 180 days **Non-performing loans (loss)** Loans past due more than 360 days
Ukraine [16]	**Non-performing loans**: – Loans past due from 90 days or more (30 days for debtor banks) – It is unlikely that the debt will be repaid in full without the sale of collateral (irrespective of any overdue amount or the number of days past due)[3]
Kazakhstan[4] [4]	**Non-performing loans**: - Loans past due from 90 days or more

Source: Internet resources, regulations in the countries

[3] This definition complies with recommendations of the International Monetary Fund
[4] The definition is used in the supervisory practice

ROBUSTNESS TO MACROECONOMIC OUTLIERS OF SEASONALLY ADJUSTED INFLATION

Khakimzhanov S. T. – Head of the Research and Analysis Department of the National Bank of Kazakhstan

Beisembetov Y.I. - analyst at «Quantum Capital» Ltd

Mukhambetzhanova D.Zh. - leading specialist analyst of the financial and real assets market analysis department of the Financial Stability and Research Department of the National Bank of Kazakhstan

In this paper, we compare robustness of estimates of seasonal factors of Kazakhstan's inflation when using various seasonal adjustment methods, including methods that take into account one-off outliers and macroeconomic shocks to inflation. Nonparametric tests revealed strong seasonality in Kazakhstan's monthly inflation, but it is also subject to rare but severe shocks which pass-through from international prices and exchange rate shocks. Analysis of revisions of seasonally adjusted inflation and seasonal factors indicated substantial bias around the outliers, which lead to subsequent revisions an order of magnitude greater than for non-outliers. This effect could hinder the adoption of deseasonalized estimates of inflation and would require the use of custom-built methods of seasonal adjustment that use information from contemporaneous macroeconomic data to decompose an outlier into a shock to the trend and a shock to seasonal pattern. In the absence of suitable decomposition methods, procedures for publishing seasonally adjusted inflation may need to be accompanied by estimates of confidence interval to encourage more caution in interpreting the estimates that are contemporaneous to the outlier and more conservatism in revising the estimates that were obtained in the periods preceding the outlier.

Key Words: inflation, seasonal adjustment, seasonality tests.
JEL-Classification: C19, E31, E37.

Preamble

Decomposition of the seasonal component of macroeconomic variables gives a more accurate and timely idea of an invariable component, useful in macroeconomic forecasting and policy. Seasonal adjustment is widely and routinely used in the practice of statistical authorities around the world. Analysis of inflation and short-term price dynamics is important for timely monetary policy response. The publication and the use of the seasonally adjusted data contributes to better understanding of short-term changes in the indicator and are of interest for policymaking, business cycle analysis and forecasting.

The choice of seasonal adjustment methodology can affect the accuracy of the input into the forecast models and, therefore, the quality of policy decisions. Typically, macroeconomic policy authorities accomplish this by using standard seasonal adjustment packages.

This paper analyzes the methods used in carrying out the seasonal adjustment, as well as statistical tests that determine its presence. As the test subject, we chose CPI inflation because it has a pronounced seasonal pattern, experiences predictable shocks to the trend due to pass through, and because of its policy relevance under the inflation targeting regime. Seasonal adjustment and subsequent analysis of the dynamics of seasonal factors were carried out based on the monthly data from January 1996 to December 2020.

The results of the study are meant to improve interpretation of inflation data flow for the conduct of monetary policy and to improve the efficiency of production and dissemination of seasonally adjusted data.

The paper consists of the following parts. The first section analyzes the literature on detection of seasonality and seasonal adjustment. The second section describes the data. The third section presents statistical tests to detect and measure seasonality of inflation in Kazakhstan. The fourth section is devoted to the development and analysis of seasonal adjustment methods that are robust to macroeconomic outliers. The fifth section includes an analysis of revision errors and the stability of seasonal factors, what causes them, and compares various methods of seasonal adjustment based on these criteria and Kazakhstan data. Conclusion, presents the main findings.

1. Methodology

Seasonal adjustment methods are the methods for detection of systematic seasonal effects and correction for said effects in reporting and in the use of the economic variables. Systematic intra-annual fluctuations due to the change of seasons (weather conditions, day length, temperature), rhythm of production processes, periods of mass vacations, etc. (Andreev A. et al., 2020). Seasonal adjustment filters out, albeit imperfectly, seasonal effects, which allows for better signal extraction at high frequency. Seasonally adjusted data are widely used in international practice by statistical and macroeconomic policy authorities. There is a wide range of software solutions and statistical algorithms for identifying a seasonal component.

1.1 Seasonality Tests

In addition to seasonal adjustment methods, this paper describes the tests used to detect the presence of seasonality in the CPI series. The trends observed in time series can be identified in a variety of ways, mainly by ranking the observations. Three tests were used in this study: the Kruskal-Wallis test, the Wilcoxon test, and the nonparametric test.

The Kruskal-Wallis test checks the median equality in several samples. This test is based on the ranks of observations, so any monotonic transformation of the measurement scale does not affect its results. Under the null hypothesis, the Kruskal-Wallis test assumes that different samples were taken from the same distribution or from distributions with the same medians.

The Wilcoxon signed-ranks test is used to test the differences between two samples of paired or independent measurements in terms of any quantitative criterion measured on a continuous or ordered metric scale. This test compares absolute values of the severity of bias in one direction or another. It also uses ranking to compare the sum of ranks for specific months. In case of more intensive bias in one direction, the bias in the opposite direction would have a much lower sum of ranks of the absolute values than it could be in case of random changes. The null hypothesis in this test is the assumption that the difference between paired observations follows a symmetric distribution around zero.

The nonparametric test uses rolling ranking with a moving 12-month interval and aggregating the resulting ranks for each month. This test uses the assumption that the difference between the sums of such ranks for each pair of months has a normal distribution with $\mu = 0$ and $\sigma^2 = 2 * 12 * N$ parameters, where N is the number of ranks included into the aggregation by months. Accordingly, the assumption that the difference between the aggregated ranks is 0 for each pair of months is used as the null hypothesis.

1.2. Seasonal Adjustment

After detection of seasonality in the original data series, the next step is to select a seasonal adjustment method. The most commonly used seasonal adjustment methods are X-12 ARIMA and TRAMO/SEATS. The X-12 method was designed by the US Bureau of Statistics and is a modification of the X-11 ARIMA method. Seasonal adjustment with the use of X-12-ARIMA method was described in the paper “New Capabilities and Methods of the X-12-ARIMA Seasonal-Adjustment Program” (Findley, 1998).

In the first part of seasonal adjustment, the RegARIMA model (linear regression model with ARIMA time series errors) is used to get rid of nonlinearities in the series, including outliers and calendar effects. In this paper, the RegARIMA model is used to expand the series using forecasts of future and past values of the series.

In the second part of seasonal adjustment, an extended version of the X11 algorithm is used to decompose time series into trend-cyclical, seasonal and irregular components by applying the moving average filters. RegARIMA model is a combination of the ARIMA model and regression model.

The TRAMO-SEATS method is an alternative algorithm for seasonal adjustment (Maravall A., Gomez V., 1992). Unlike methods of the X-11 family, TRAMO-SEATS is based on construction of an individual model for each processed time series, whereas in X-11 and X-12 ARIMA methods, with the given parameters, all time series are processed using the same linear filters.

TRAMO, or Time Series Regression with ARIMA Noise, Missing Observations and Outliers, performs preliminary processing of the series by constructing a regression for calendar variables with residuals in the form of an ARIMA model, and incorporates and corrects different types of outliers. SEATS, or Signal Extraction in ARIMA Times Series, carries out deseasonalization of the results (residuals) generated by the TRAMO. The residuals obtained during regression of original data into calendar variables are presented in the form of an additive model.

TRAMO-SEATS includes part of the stochastic component in the estimate of seasonal factor, while in X-12 ARIMA the stochastic component is fully included in the irregular I_t. component. As a result, the X-12 ARIMA residue has more variance than the TRAMO-SEATS residue. However, this does not mean that TRAMO-SEATS gives a more accurate estimate than X-12, as, for example, is argued in the literature (Andreev A. et al., 2020).

However, despite the discrepancies, results of the two algorithms have a minor difference. So, Bessonov V. and Petronovich A. (2013) in their work “Seasonal Adjustment as a Source of False Signals” note that the aberrations that occur in the vicinity of the crisis are of a similar nature. Both algorithms can generate false signals that distort the dynamics of the adjusted series.

2. Data

The data on inflation measured by Consumer Price Index (CPI) was obtained from the website of the Bureau of National Statistics of the Agency for Strategic Planning and Reforms of the Republic of Kazakhstan[5]. In winter and autumn, the CPI inflation is generally higher than in spring and summer. In the sample covering the period from 1996 to 2020, the highest monthly inflation occurs in January (1.14 pp), November (1.12 pp) and October (1.08 pp), and the lowest – in August (0.16 pp). With a range of 0.98 pp between January and August, seasonality makes a significant contribution to inflation volatility.

Inflation in Kazakhstan has a pronounced seasonality, which is especially manifested in food products. In addition, the seasonal pattern itself is also subject to changes.

3. Seasonality Tests

The nonparametric test used to detect seasonality does not require strict assumptions and is more flexible than parametric tests. Our nonparametric test is based on the ranks of observations for certain periods (months). This approach implies that a random variable R_t, which denotes the rank of the consumer price index X_t for a certain month t over the 12-month interval $[t-5; t+6]$, has a multi-nomial distribution with parameters $n = 12$ and $k = 12$, where n is the number of tests (the number of months in the reviewed period at the time t), and k is the number of possible outcomes of interest (the range of possible values when ranking from 1 to 12). In order to perform the statistical analysis of these series, an assumption is required that observations $x_1, x_2, \dots, x_n$ of the consumer price index X_t and, respectively, their ranks $r_1, r_2, \dots, r_n$ are distributed randomly. This assumption of randomness will be taken as the null hypothesis of our test. Thus, rejection of the null hypothesis will mean the existence of a certain trend, indicating the presence of seasonality.

[5] The data comes from Taldau information and analytical system

The reviewed sample included the CPI values from January 1991 through December 2020. However, for variable R_t, which denotes the CPI rank at the time t, the sample size would differ from the CPI sample since the ranking of observation X_t is performed for the time interval $[t-5; t+6]$. Thus, for example, to determine the CPI rank for June 1991, the period from January 1991 to December 1991 needs to be reviewed. Therefore, the sample period for R_t is June 1991-June 2020.

After the ranks are determined, the next step would be to aggregate them by month. For each month m, $1 \leq m \leq 12$, the sum of ranks for the period from July 1991 to June 2020, Z_m , was calculated (the rank for June 1991 was not included in the aggregation to ensure the same number of observations for each month). Further, for each of the 66 month pairs, the difference between their respective aggregated rank sums, $Z_m - Z_n$, $1 \leq m \leq 12$, $1 \leq n \leq 12$, $m \neq n$, was calculated.

The analysis is based on the assumption that the data in the $Z_m - Z_n$ difference is normally distributed with $\mu = 0$ and $\sigma^2 = 2 * 12 * N$ parameters, where N is the number of ranks included in the aggregation by months ($N = 29$). Таким образом, используя тест для разницы между двумя средними значениями для генеральных совокупностей, имеющих нормальное распределение, можно сделать вывод относительно наличия статистически значимой разницы между двумя месяцами. Каждая возможная пара месяцев была протестирована на уровнях значимости 10%, 5% и 1%. Thus, using the test for the difference between the two means for populations with normal distribution, a conclusion can be made that there is a statistically significant difference between the two months. Every possible pair of months has been tested at the 10%, 5%, and 1% confidence levels. For each month, the number of months was recorded, where the difference was statistically significant at each of these three confidence levels. So, the month with the largest number of statistically significant differences with other months is August.

Also, for each confidence level, the L statistics was calculated, which denotes the total number of statistically significant differences for all pairs of months.

This procedure was performed for different groups of goods and services, as well as for different sampling periods. In addition to the Jul. 1991-Jun. 2020 sample, the following samples were studied: Jul. 1997-Jun. 2020, Jul. 1991-Jun. 1999, Jul. 1999-Jun. 2010, and Jul. 2008-Jun. 2020.

The Wilcoxon's test is a nonparametric statistical test of whether two samples come from different populations. For each pair of samples, the test statistic is computed by first ranking the observations, computing the difference in ranks, and then computing the sum of the signed differences in ranks. Under the null hypothesis, the test statistic is distributed symmetrically around zero.

To test seasonality by the Wilcoxon test, first of all, the series for paired observations need to be determined. If the null hypothesis of a symmetric distribution of differences around zero is rejected for the two series, this would indicate the existence of a bias towards one series and, therefore, the presence of seasonality. The values of consumer price indices $cpi_{i,j}$ were tested, where i denotes the year, and j – the month of the observation. Therefore, in order to test prices for the presence of seasonality, all such possible pairs of months j and k were selected as the compared series, that $1 \leq j \leq 12$, $1 \leq k \leq 12$, $j \neq k$. For each month j, the $cpi_{i,j}$ series were constructed, where $1991 \leq i \leq 2020$.

Therefore, 66 Wilcoxon tests were performed for all possible pairs of months at 5% and 1% confidence levels. A similar procedure was carried out for the constituent price indices for food products, non-food products and paid services.

According to the test, the null hypothesis of a symmetric distribution of the difference between months was rejected at a confidence level of 5% for 42 pairs of months in the general consumer price index, 48 pairs of months in the consumer price index for food products, 7 pairs of months in the consumer price index for non-food products, and 19 pairs of months in the consumer price index for paid services. At the 1% level, the hypothesis was rejected for 34 pairs of months in the general consumer price index, 38 pairs of months in the consumer food price index, 0 pairs of months in the consumer price index for non-food products, and 8 pairs of months in the consumer price index for paid services. Thus, based on the Wilcoxon criterion, food price index is the constituent index most prone to seasonality.

Test results may vary depending on the sample period. A significant difference in test results between the samples may indicate a change in seasonality. For example, in the period from 1991 to 1999, the number of month pairs for which the hypothesis of symmetric difference was rejected, was substantially smaller than for the intervals of 1999-2010 and 2008-2020 for all CPIs. At the same time, when studying the period of 1997-2020 for the three groups of CPI (that is, excluding the first six years from the original sample), the number of month pairs for which the difference was statistically significant was greater than for the period of 1991-2020. Thus, based on the CPI data, an observation can be made that in the 1990s the number of month pairs with a statistically significant difference was smaller than in the next period, thus indicating weaker seasonal effects.

As for the intervals of 1999-2010 and 2008-2020, in the latter the seasonality was less pronounced among non-food products and paid services. The seasonal effect on food prices has not changed.

The Kruskal-Wallis test is designed to test the equality of medians of several samples. This test is a multivariate generalization of the Wilcoxon-Mann-Whitney test. The Kruskal-Wallis criterion is a rank; therefore, it is invariant to any monotonic transformation of the scale. Unlike the Wilcoxon test, this test is used to compare three or more samples and to test null hypotheses of different samples coming from the same distribution, or from distributions with the same medians. Thus, when conducting the Kruskal-Wallis test, one should decompose the series of CPI data into groups of observations by months. Consequently, there will be 12 groups in the sample, and refuting the null hypothesis would mean an unequal distribution of values in the population.

Four Kruskal-Wallis tests were conducted for each of the CPI groups: general CPI, CPI for food products, CPI for non-food products, and CPI for paid services. For the general CPI, the F-statistic was 58.05 with a p-value close to zero. Thus, for the general CPI, the null hypothesis that each group (month) has the same distribution of values in the population must be strictly rejected, which indicates the presence of seasonality. For the consumer food price index, the p-value is also close to zero, which means a strong seasonal effect on food prices. For non-food products, the p-value is 0.0634. Thus, for non-food products, the null hypothesis cannot be rejected at the 5% level, which indicates a weak seasonal effect on this group of products. The p-value for the CPI for paid services is lower than for non-food products and is equal to 0.0156, thus showing a moderate seasonal effect on paid services.

Overall, the Wilcoxon and Kruskal-Wallis test results are similar and suggest a strong seasonal effect on food products. The least seasonally prone group of goods is non-food products, whereas the influence of seasonality on paid services is moderate.

When comparing the results of the Kruskal-Wallis test between periods, just as in the Wilcoxon test, the period with the least significant test results is 1991-1999. In this period, the null hypothesis for all CPI groups will not be rejected at the 10% level. At the same time, for the 1997-2020 sample, the test results turned out to be more significant than for the 1991-2020 period. In the 1999-2010 period, the null hypothesis was rejected at the level of 5% for all product groups. For the 2008-2020 period, similar to the Wilcoxon test, the group of non-food products had the least significant seasonality.

Thus, in general, all three tests prove that there is a seasonal factor in Kazakhstan, with the varying degrees for different groups of goods. At the same time, the seasonal factor becomes more significant over time for the general CPI.

4. Seasonal Adjustment Methodology

Seasonal adjustments were carried out based on the CPI aggregate and its three components. Eight methods were used for seasonal adjustment of each series, using either X-12 or TRAMO/SEATS, or their variants:

1. *X-12*. Under the X-12 method, a log additive model with the addition of a constant as a regressor and the ARIMA specification (1 0 2)(1 0 1) was used.
2. *X-13 without outliers*. Under the X-13 method without outliers, an additive model with the ARIMA specification (0 1 1) (0 1 1) with a 3x3 seasonal moving average filter and a forecast and retrospection was used. The sampling period for the ARIMA model is Jan 1999-Dec 2020.
3. *TRAMO/SEATS without outliers*. Seasonal adjustment by the TRAMO/SEATS method was carried out with the successive application of the TRAMO model, followed by the SEATS model and a forecast horizon of 8 months.
4. *X-13 with outliers*. The number of outliers during the observed period varied depending on the series. For example, in the series of general CPI and food CPI, outliers were observed in 1999, 2007 and 2015. Various outlier combinations have been used in the models that include such outliers. In addition to combinations including all outliers, we also used the combinations where the outliers observed in a particular year were excluded. For the general CPI and food CPI, we used both the combination that includes all outliers (1) and the combinations where 1999, 2007 or 2015 was excluded:
   1) 04.1999, 05.1999, 06.1999, 10.2007, 11.2007, 10.2015, 11.2015;
   2) 10.2007, 11.2007, 10.2015, 11.2015;
   3) 04.1999, 05.1999, 06.1999, 10.2015, 11.2015;
   4) 04.1999, 05.1999, 06.1999, 10.2007, 11.2007.

   There were less outliers in the CPI series for non-food products. Outliers were observed in 1999 and 2015. The following outlier combinations were studied:
   5) 04.1999, 06.1999, 10.2015, 11.2015;
   6) 04.1999, 06.1999;
   7) 10.2015, 11.2015.

   In the series of CPI for paid services, outliers were observed in 2000, 2007, 2010 and 2019. The following combinations were used for such series:
   8) 01.2000, 10.2007, 01.2010, 02.2019;
   9) 10.2007, 01.2010, 02.2019;
   10) 01.2000, 01.2010, 02.2019;
   11) 01.2000, 10.2007, 02.2019;
   12) 01.2000, 10.2007, 01.2010.
5. *TRAMO/SEATS with outliers.* This method also used the above combinations of outliers. In seasonal adjustment with the X-13 algorithm, the ARIMA model (0 1 1)(0 1 1) was also used with 3x3 seasonal moving average filter and addition of forecast and retrospection. In the TRAMO/SEATS method, these combinations were indicated as additive outliers (one-point jumps in the time series). Just as in the TRAMO/SEATS method without outliers, the SEATS model was applied after the TRAMO model and had a forecast horizon of 8 months.
6. *TRAMO/SEATS with predetermined variables*. In the TRAMO/SEATS method with predetermined variables, $dlog(usdkzt)$ and $dlog(fao\ f)$ macro variables were chosen, where:

   $dlog(usdkzt_t) = \log(usdkzt_t) - \log(usdkzt_{t-1})$,

   $dlog(fao\ f_t) = \log(fao\ f_t) - \log(fao\ f_{t-1})$.

   $usdkzt_t$ is an average monthly exchange rate of the US dollar against the tenge for month *t*,

   $fao\ f_t$ – the FAO Food Index (Food and Agriculture Organization of the United Nations) in the month t.

7. *Iterative algorithm with predetermined macroeconomic variables*. The following steps have been taken in this process:
   1) The CPI series was deseasonalized by the X-12 algorithm with the use of the log additive model with the ARIMA (1 0 2)(1 0 1) specification and addition of a constant as a regressor;
   2) Regression coefficients were computed by using the least squares method, where a seasonally adjusted CPI (cpi_sa) served as the dependent variable, and regressors – $dlog(usdkzt)$ and $dlog(fao\ f)$ – as regressors;
   3) A new series is generated by way of the following equation:
      $x_i = x_{i-1} - \beta_1 * dlog(usdkzt) - \beta_2 * dlog(fao\ f)$, where:
      x_0 – a CPI level,
      β_1 – the coefficient of regression for variable $dlog(usdkzt)$,
      β_2 – the coefficient of regression for variable $dlog(fao\ f)$.
   4) $RMSE(Z_i, Z_{i-1})$ is computed, where:
      $Z_i = \frac{x_i}{x_0}$.
   5) This process is reiterated until one of the following conditions is met:
      - $RMSE(Z_i, Z_{i-1}) < 1\%$,
      - $k \geq 5$, where k – is the number of iterations in the given process.
8. *The iterative algorithm with predetermined macroeconomic variables and the use of GARCH model*. This process was similar for the method with the use of GARCH model except that in the step (3), instead of the least squares method, coefficients were computed by using the GARCH method.

After seasonal adjustment by the methods described above, forecast values were computed for each method and for each CPI series, where the period of Jan 1996-Dec 2010 was chosen as the training sample, and Jan 2011-Dec 2020 was chosen as the predicted sample. The forecast was made by using linear regression equations, where the baseline CPI level is the dependent variable and the seasonally adjusted CPI level – the independent variable. The RMSE metric (Root-mean-square deviation) was used as a measure of the proximity of forecast values to the actual ones. (Table 1):

$RMSE = \sqrt{\frac{\sum_{t=1}^{n}(cpi_{fcst_t} - cpi_{actual_t})^2}{n}}$, where:

cpi_{fcst_t} – a CPI forecast for period t,

cpi_{actual_t} – an actual CPI for period t,

n – the number of periods in the sample.

This metric aggregates the forecast errors for different points in time into one standardized value. Thus, under this criterion, you can choose the most optimal method of seasonal adjustment in terms of the forecast accuracy.

Table 1. RMSE Values on the CPI Series and the Seasonal Adjustment Method

No.	Method	cpi	cpi_f	cpi_n	cpi_s
1	X-12	0.001464	0.002990	0.001527	0.001686
2	X-13 without outliers	0.001570	0.003158	0.001780	0.001784
3	TRAMO/SEATS without outliers	0.001278	0.002565	-	0.001468
4	X-13 with outliers (1)	0.001383	0.002797	-	-
5	X-13 with outliers (2)	0.001379	0.002789	-	-
6	X-13 with outliers (3)	0.001385	0.002797	-	-
7	X-13 with outliers (4)	0.001573	0.003171	-	-
8	X-13 with outliers (5)	-	-	0.000789	-
9	X-13 with outliers (6)	-	-	0.000735	-

10	X-13 with outliers (7)	-	-	0.001779	-
11	X-13 with outliers (8)	-	-	-	0.001714
12	X-13 with outliers (9)	-	-	-	0.001724
13	X-13 with outliers (10)	-	-	-	0.001722
14	X-13 with outliers (11)	-	-	-	0.001797
15	X-13 with outliers (12)	-	-	-	0.001713
16	TRAMO/SEATS with outliers (1)	0.001713	0.003194	-	-
17	TRAMO/SEATS with outliers (2)	0.001713	0.003194	-	-
18	TRAMO/SEATS with outliers (3)	0.001713	0.003194	-	-
19	TRAMO/SEATS with outliers (4)	0.001762	0.003226	-	-
20	TRAMO/SEATS with outliers (5)	-	-	-	-
21	TRAMO/SEATS with outliers (6)	-	-	-	-
22	TRAMO/SEATS with outliers (7)	-	-	-	-
23	TRAMO/SEATS with outliers (8)	-	-	-	0.001880
24	TRAMO/SEATS with outliers (9)	-	-	-	0.001880
25	TRAMO/SEATS with outliers (10)	-	-	-	0.001880
26	TRAMO/SEATS with outliers (11)	-	-	-	0.001880
27	TRAMO/SEATS with outliers (12)	-	-	-	0.001867
28	TRAMO/SEATS with predetermined macroeconomic variables	0.001362	2.69E-07	0.001015	0.001536
29	Iterative algorithm with predetermined macroeconomic variables	0.002237	0.003368	0.003333	0.001721
30	Iterative algorithm with predetermined macroeconomic variables and the use of GARCH model	0.001920	0.003121	0.002805	0.001740

Notes: 1) the numbers for outlier combinations are in line with the numbering presented on page 8; cpi – general CPI, cpi_f – food CPI, cpi_n – CPI for non-food products, and cpi_s – CPI for paid services; 2) there are empty fields for methods No.20, 21, 22 and for method No.3 in the CPI series for non-food products since due to a low seasonal effect on this group of goods, the TRAMO regression without macro variables does not work for the cpi_n series.

5. Revision Errors

The obtained estimates of seasonally adjusted inflation can be used for the macroeconomic analysis. However, in practice, the use of seasonally adjusted data is complicated by the fact that in analytics, the decision-making requires that potential error introduced by the adjustment methods as well as the subsequent revision of seasonally adjusted series are taken into account. Thus, with the appearance of new input, the earlier seasonally adjusted estimates are revised. However, with the addition of more periods, i.e. with an increase in the length of the analyzed time series, it is assumed that robustness will appear in the seasonally adjusted estimates.

Seasonally adjusted data is revised for two main reasons. First, seasonally adjusted data is revised to improve the coverage of the set of available information and to update the actual data. Second, as new information is added, characteristics of seasonal adjustment filters improve, and the seasonal model's assessment becomes more reliable. Nonetheless, when seasonal adjustment with the use of asymmetric filters at the ends of the time series (X-12-ARIMA model) is performed, even one additional observation affects the current estimates of the seasonal and trend-cyclical components and could lead to revision of seasonally adjusted data over several years (tail wagging effect). Standard seasonal adjustment parameters imply a symmetric filter that uses 6 to 10 years of raw data to produce a final seasonally adjusted estimate. For seasonal adjustment, skewed filters are used at the end of the series because they use fewer observations after the control point than those that precede it. It takes up to 5 years to achieve final adjustment using standard options (Tiller and Evans, 2017). As a result, previous seasonally adjusted estimates are updated with the addition of a new value to the time series, which can confuse users of such information. Thus, the main challenge in publishing seasonally adjusted data is to balance the need to obtain the best seasonally adjusted data and its robustness over time.

To determine the stability of the obtained seasonally adjusted estimates, the revision error reflecting a change in the seasonally adjusted time series with the introduction of new observations of inflation was computed. For the basic inflation series π_t, where $t = 1, \dots, T$, we determine the seasonally adjusted inflation $\pi_{t,s}^{sa}$ where $t \leq s \leq T$.

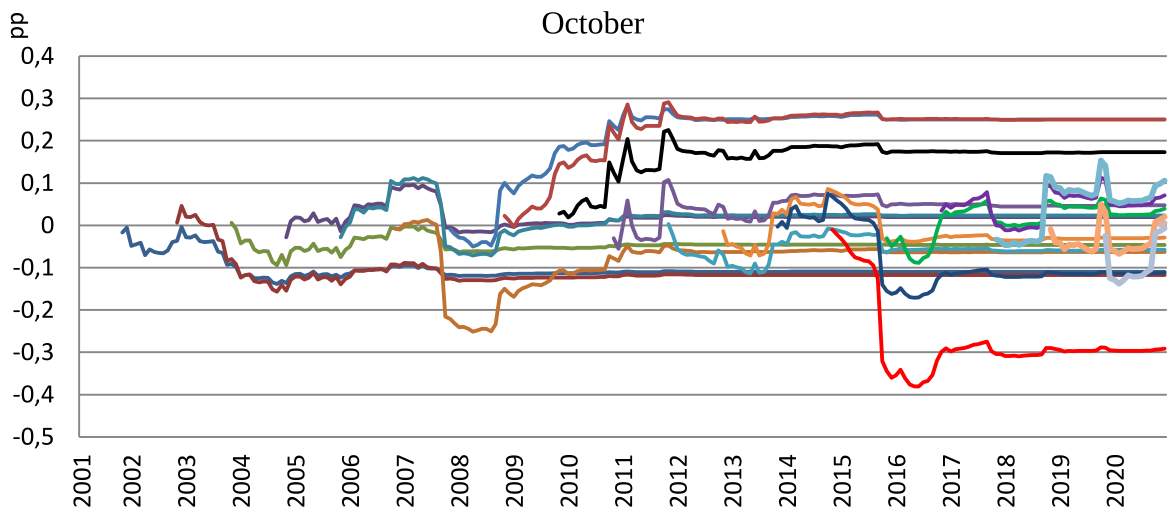
$$R_{t,s} = {\pi^{sa}}_{t,s} - {\pi^{sa}}_{t,t}, \text{ where}$$

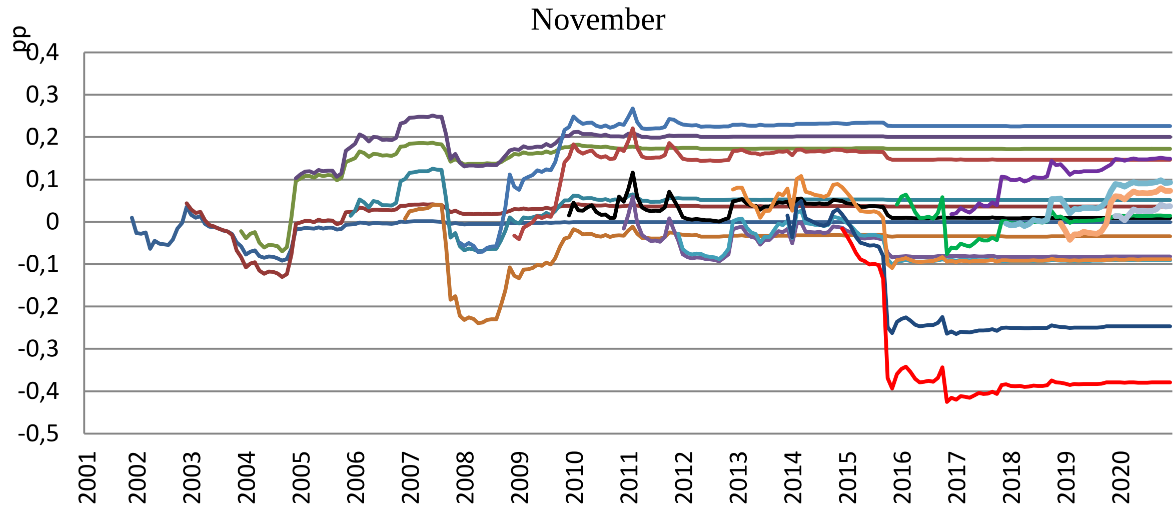
$R_{t,s}$	–	Revision error of seasonally adjusted data
$\pi_{t,s}^{sa}$	–	The seasonally adjusted inflation in month t, estimated based on the data available at the date $s \geq t$, i.e. on the basis of the $\{\pi_k\}_{k=1}^{s}$ series
${\pi^{sa}}_{t,t}$	–	The first seasonal adjusted value of inflation
t	–	The date of inflation observation
s	–	The date of the seasonal adjustment

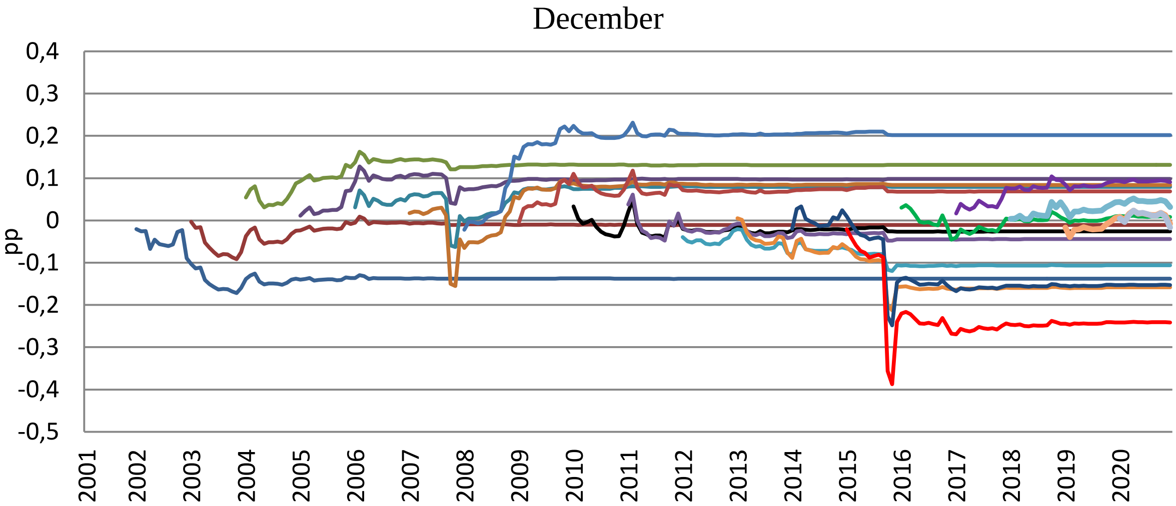
This study used a strategy of parallel adjustment of revisions of seasonally adjusted data, that is, with the addition of a new month, seasonal adjustment of the available time series was repeated. From a theoretical point of view, it is desirable that initial seasonally adjusted estimates be as close as possible to the improved estimates obtained after more data becomes available.

With historical data on inflation, the initial five-year series (Jan 1996 - Dec 2000) was updated with new data every month. The revision error analysis is carried out from January 2001 to December 2020 (Figure 1). Our computations have shown that when new information is added, revision errors are extremely unstable. So, a revision error becomes insignificant after 5-6 years (it is approximately at the same level). This effect is manifested in the instability of estimates of the seasonally adjusted series on its right end when the initial data for the next months or quarters are added. However, some shocks bring changes in the dynamics of seasonally adjusted inflation even after a long time, which, in our opinion, is largely due to the pass-through from one-time shocks to the seasonally adjusted series.

Figure 1. Revision errors by months obtained by using the X-12-ARIMA method







Source: the authors' estimates

Note: diagrams of revision errors by months are presented in Appendix 1

According to the results obtained, revision errors have a certain pattern for each month (Appendix 1). Thus, there is either an increase or reduction of the revision error for each analyzed month in the same period.

In many ways, a revision error is related to the fact that we account for seasonality incorrectly. Thus, it can be misleading to frequently update seasonally adjusted data for the same periods given the revisions made. The stability in publishing seasonally adjusted data is important for making interpretation of seasonally adjusted data feasible and ensuring its accuracy.

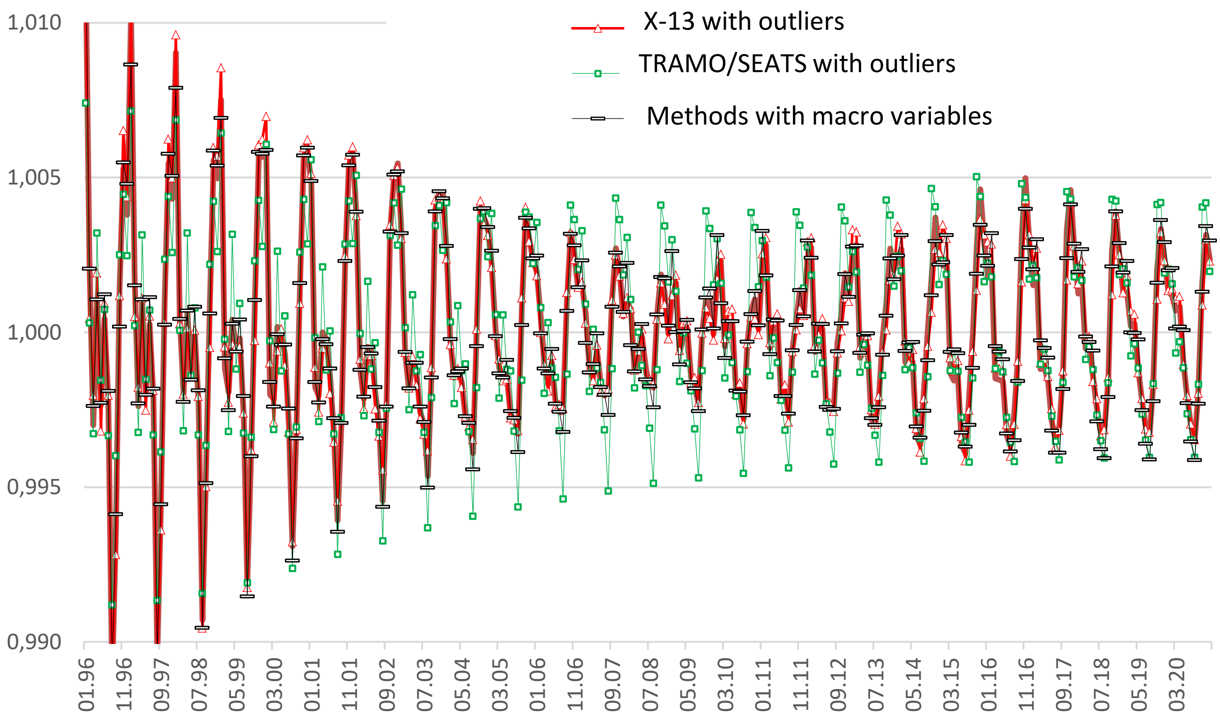
6. Discussion of Results

Seasonal adjustments by various methods enabled to analyze the seasonal factor's dynamics depending on the method. In particular, it is interesting how macro outliers and predetermined variables added to the seasonal adjustment algorithm affect the seasonal pattern. These outliers are understandable, since their existence is caused by non-seasonal macroeconomic factors of a one-time nature. Despite a similar plot of the dynamics of seasonal factor (Figure 2), the amplitude of its fluctuations may differ depending on the method and period. The pattern and amplitude of the seasonal factor changes at a mid-term frequency: the range of factors was narrowing during the period from 1996 to 2009-2011, was expanding again until 2014-2016, and began to narrow again in 2017-2021. Appendix 2 presents seasonal factor diagrams for each month. Appendix 3 shows the seasonal pattern for individual years with an interval of 5 years.

To analyze the seasonal effect of macroeconomic outliers and variables, all series of seasonal factors generated as a result of seasonal adjustment by various methods were divided into 4 types:

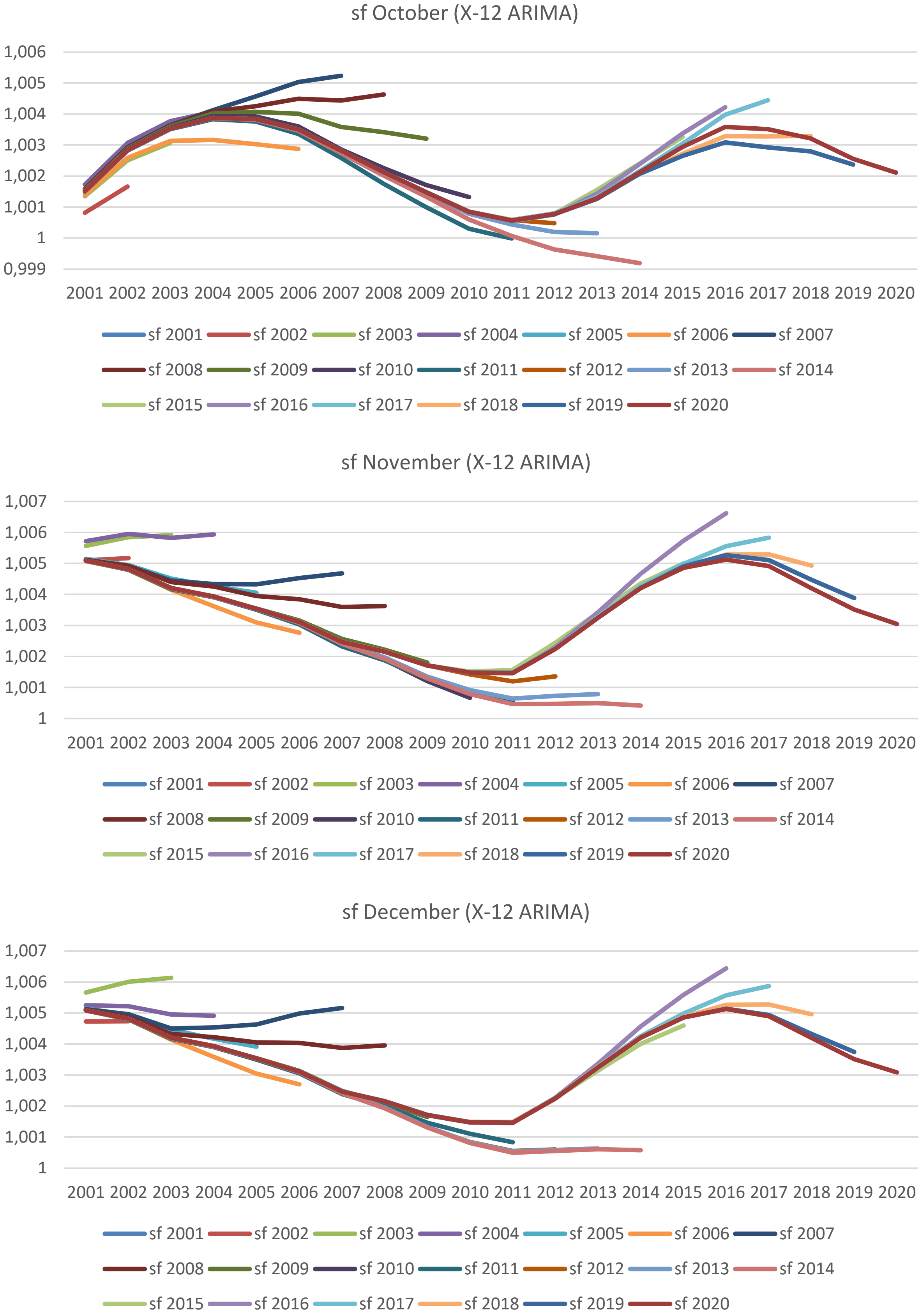
1) Series generated as a result of the methods without outliers and variables ((1), (2) and (3) in Table 2),
2) Series generated as a result of the X-13 method with outliers ((4), (5), (6) and (7) in Table 2),
3) Series generated as a result of the TRAMO/SEATS method with outliers ((16), (17), (18) and (19) in Table 2),
4) Series generated as a result of the methods with outliers and macro variables ((28), (29) and (30) in Table 2).

Figure 2. Stability of the seasonal pattern and seasonal adjustment methods



The dynamics of seasonal factor by months including its revisions also attracts interest. At times of strong inflationary surges, the dynamics of seasonal factor by months can change the direction, which indicates the impact of false signals during a crisis. Figure 3 shows synchronous estimates of the seasonal factor for 3 months, made at the time when the sample ends. Just as with the computation of revision errors, parallel revision corrections are used. Thus, starting from 2001, the seasonal factor series is computed 20 times with the addition of new data for each year. The study of the seasonal factor for October shows that a significant rise in inflation in October 2015 caused by the pass-through effect with a spike in the exchange rate of the US dollar against the tenge influenced the dynamics of seasonal factor over the previous several years. The impact of inflation surge in 2015 can be traced in November as well. With subsequent revisions, the dynamics of seasonal factor is smoothed out. The opposite situation is observed with the revision of the seasonal factor in 2008-2009, when, due to deflation, the dynamics of seasonal factor for December decreases.

Figure 3. Seasonal factor depending on the CPI assessment date, X-12 ARIMA



To assess a change in the dynamics of seasonal factor over time, the entire period from 1996 to 2020 was divided into three approximately equal intervals for assessment of the change in the amplitude of fluctuations: Jan. 1996-Dec 2004, Jan 2005-Dec 2012, Jan 2013-Dec 2020. The standard deviation was computed for each method and for each period. To aggregate the obtained standard deviations for the above types, the mean standard deviation among the methods within each type was computed (Table 2).

For all CPIs, the least volatile series of seasonal factors for the entire sample were those obtained with the seasonal adjustment methods by using macro variables. Moreover, the most volatile period for each type was the period from 1996 to 2004. During that period, prices were generally less stable, which was reflected in their components including the seasonal factor. It is also noteworthy that the inclusion of certain outliers in the seasonal adjustment algorithms (for both X-12 and TRAMO/SEATS) increases the seasonal factor's variance. The exception is the group of non-food products. In general, the seasonal factor series obtained by the seasonal adjustment algorithms that include macroeconomic variables do not show that they are more robust statistically compared to other methods.

Table 2. Standard deviations of the seasonal factor by periods and methods

	Methods without outliers	X-13 with outliers	TRAMO/SEATS with outliers	Methods with macro variables
1996-2020	0.00304	0.00305	0.00311	0.00302
1996-2004	0.00421	0.00427	0.00372	0.0041
2005-2012	0.00174	0.00171	0.00270	0.00185
2013-2020	0.00242	0.0024	0.00276	0.00249

The study of the seasonal factor's volatility by months showed that the months with the greatest variance of the seasonal factor for the general CPI and the food CPI are January and August. At the same time, in January the values of the seasonal factor are high, while in August they are low. Thus, fluctuations in the seasonal factor are cyclical but the array of their peaks varies from year to year.

As for the comparison of methods, for almost every month, the standard deviations of seasonal factors obtained by methods from the TRAMO/SEATS class with macro outliers were lower than those produced by other methods (Appendix 4), which can also be seen in the diagrams of seasonal factors by months (Appendix 2). Thus, the variability of the seasonal factor amplitude is the lowest for this particular type. It would be counterproductive to use the same outlier combinations for the X-13 method. The estimates produced by the TRAMO/SEATS methods are more robust; however, with their use, the ability to identify rapid changes in the seasonal pattern is being lost.

The next criterion for evaluating the seasonal adjustment method is the proximity of forecast values to the actual ones. Here, a comparison of both long-term and short-term forecasts takes place. The long-term forecast is assessed by the proximity of the entire range of forecast values to the range of actual values. To assess this proximity, RMSE statistics were calculated for each method (Table 3). Then, the methods were grouped according to the principle described above, and the average RMSE value was computed for each group. The values of aggregated RMSE statistics show different results for different CPI series. For example, for the general CPI and CPI for non-food products, the group of X-13 methods with outliers had the lowest mean RMSE value. In assessing the food CPI, the methods with macroeconomic variables had the values closest to the actual ones. Algorithms without outliers and macro variables turned out to be the most optimal methods for assessing the CPI for paid services.

It is worth discussing separately how the choice of a seasonal adjustment method affects the forecast accuracy precisely at the end of the sample. For this, the CPI forecast values were computed by using a similar method, where the year 2020 only was used as a forecast sample. Mean RMSE values for assessing the proximity of forecast values to actual values for each type of seasonal adjustment are presented in the table below.

Table 3. Comparing mean RMSE for various forecast samples

Period	Name of Method	cpi	cpi_f	cpi_n	cpi_s
2011:1 - 2020:12	Methods without outliers	0.00144	0.0029	0.00165	0.00165
	X-13 with outliers	0.00143	0.00289	0.0011	0.00173
	TRAMO/SEATS with outliers	0.00173	0.0032	-	0.00188
	Methods macro variables	0.00184	0.00216	0.00238	0.00167
2020:1 - 2020:12	Methods without outliers	0.00042	0.00095	0.00025	0.00033
	X-13 with outliers	0.00041	0.001	0.00022	0.00038
	TRAMO/SEATS with outliers	0.00054	0.00102	-	0.00035
	Methods with macro variables	0.00058	0.00073	0.00072	0.00034

Note: 1) cpi – general CPI, cpi_f – food CPI, cpi_n – CPI for non-food products, cpi_s – CPI for paid services; 2) there are empty fields for the TRAMO/SEATS method with macro outliers 3 in the series of CPI for non-food products since due to low seasonal effect on this group of goods, the TRAMO regression without macro variables does not work for the cpi_n series. The mean RMSE for the methods without outliers in cpi_n was computed excluding the TRAMO/SEATS method without outliers (X-12 and X-13 methods without outliers were taken into consideration).

Thus, the results show that the relationship between the choice of a seasonal adjustment method and the proximity of forecast values to the actual values at the end of the series does not differ much from the same relationship over a wider interval (2011-2020). However, in order to assess the ability of a particular type of seasonal adjustment to influence forecast values, one should also consider how the choice of method affects the accuracy of short-term forecasts.

To assess the short-term forecast, the forecast CPI values were looked at exactly 3 months forward after the end of the training sample. That is, if the forecast sample starts from January 2011, then the forecast value for April 2011 is taken for the assessment. Further, the forecast sample is shifted one month forward (starting from February 2011), and the forecast value for May 2011 is taken for the assessment. This process is iterated until the end of the studied series. Further, for each method, the sum of squares of the differences between these forecast values and the actual ones for each forecast sample was calculated. Among the given sums of squares within each class of methods, the mean values were calculated (Table 4).

Table 4. Average amount of squared deviations of short-term forecasts from actual values

Name of Method	cpi	cpi_f	cpi_n	cpi_s
Methods without outliers	0.00062	0.00256	0.0009	0.00077
X-13 with outliers	0.00061	0.00249	-	0.00087
TRAMO/SEATS with outliers	0.0009	0.00308	0.00048	0.00095
Methods with macro variables	0.00106	0.00213	0.002	0.0008

Generally, one may suggest that the inclusion of macro outliers in the X-13 algorithm improves the forecast accuracy insignificantly, and the inclusion of the regression for macro variables in the algorithm, due to the additional noise of regressors themselves, does not bring the forecast values of inflation closer to the actual ones.

7. Conclusion

This paper described the specifics of seasonal adjustment based on inflation in Kazakhstan from 1996 to 2020. Nonparametric tests revealed strong seasonality in Kazakhstan's monthly inflation, especially in food inflation. The results of seasonal adjustment by various methods were studied in terms of seasonal volatility and forecast accuracy. The results show that it is not always practicable to use only the ARIMA specifications built into the X-12 ARIMA program.

Inflation in Kazakhstan is subject to rare but severe shocks, which a priori should not have seasonality. These macroeconomic outliers are associated with the pass-through from shocks of international prices, one-off exchange rate depreciation or its protection. Standard methods are poorly adapted to seasonal filtering of the time series with outliers, since their trend is defined as a low-frequency component, which, by definition, does not allow rapid amplitude changes. As a result, during the outlier period, an erroneous pass-through of a part of the outlier to the seasonal factor also takes place, leading to substantial adjustment in the estimates of inflation trend and seasonally adjusted inflation of the previous months. Methods that do not presume the possibility of outliers in the inflation trend do not allow effective decomposition. Volatility of estimates of seasonally adjusted inflation and the seasonal factor results in the need of substantial revisions both at the time of the outlier in relation to inflation estimates in the months closely preceding the outlier, in the corresponding month of previous years, and in the periods after the outlier.

Alternative methods, including the use of regression on macro variables were used to eliminate the effect of these shocks. In case of standard X-12 methods, the seasonal factor estimate in the month with an outlier is much more volatile than the estimate for a more typical month. The revision of the assessment accumulated over the first 2-3 years after the synchronous assessment can reach 0.4 pp. More stable estimates can be obtained by using TRAMO/SEATS methods, with a simultaneous loss of the ability to detect rapid changes in the seasonal pattern. The atheoretic detection and decomposition of outliers, without trying to explain or predict them, enables to reduce instability of the estimate, but the uncertainty in the estimate decreases only after 2-3 years. When seasonal adjustment is applied not to inflation but to its estimate based on the regression of inflation on the exchange rate and the FAO price index, it reduces the estimate bias during the periods of explained outliers, but introduces additional high-frequency noise of the regressors themselves. Attempts made to decompose macroeconomic shocks and seasonal factors were not effective enough to improve the quality of seasonal adjustment. To solve this problem, more advanced models explaining inflation and more flexible methods of seasonal adjustment are needed.

Bias errors resulting from revisions of seasonally adjusted data appeared to be statistically significant. Based on parallel seasonal adjustment, it was found out that initial revision errors are usually the largest. Further, in about five years after the date of observation of inflation, the estimates of seasonally adjusted data stabilize at the same level.

Methods used to offset the bias caused by predictable outliers were not effective enough as some of the noise in the regressor used to predict outliers passed through to the seasonal adjustment error. A negative result, in this sense, should not be discouraging. We see the ways to improve the effectiveness of seasonal adjustment based on information about the dependence of outliers and regressors, first, in improving the understanding of this relationship, and in particular, of what causes variability of lags, rates and completeness of the pass-through, and second, in developing seasonal adjustment methods taking account of information about variability of parameters of the outlier prediction model.

In the absence of suitable decomposition methods, procedures for publishing seasonally adjusted inflation may need to be accompanied by estimates of confidence interval to encourage more caution in interpreting the estimates that are contemporaneous to the outlier and more conservatism in revising the estimates that were obtained in the periods preceding the outlier.

List of References

1. Andreev A., Porshakov A., Sapova A., Shatillo Ye. (2020). Methodology of the Consumer Price Index Seasonal Adjustment of the Bank of Russia.

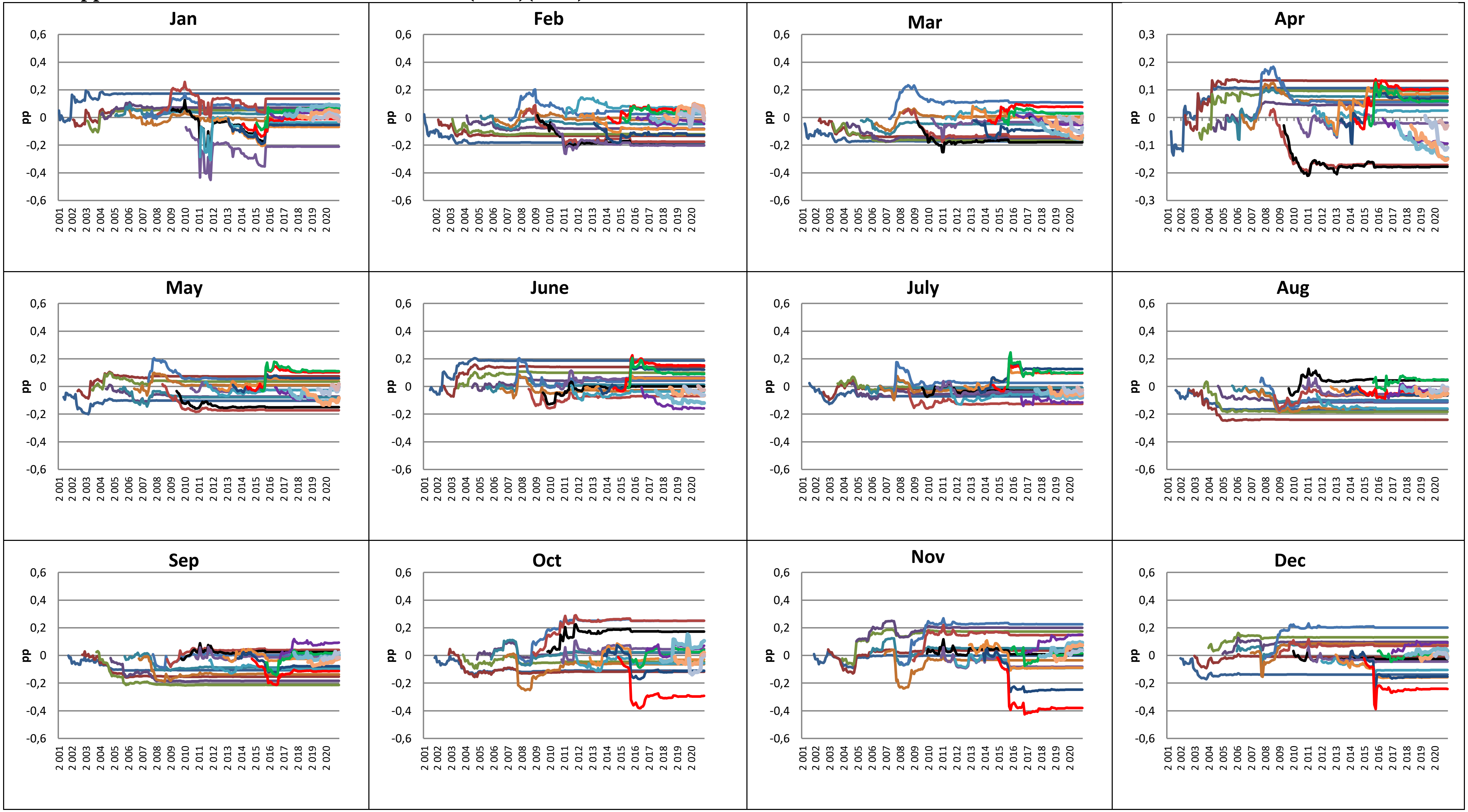
2. Bessonov V., Petronovich A. (2013). Seasonal Adjustment as the Source of False Signals.

3. Findley D. (1998). New Capabilities and Methods of the X-12-ARIMA Seasonal-Adjustment Program.

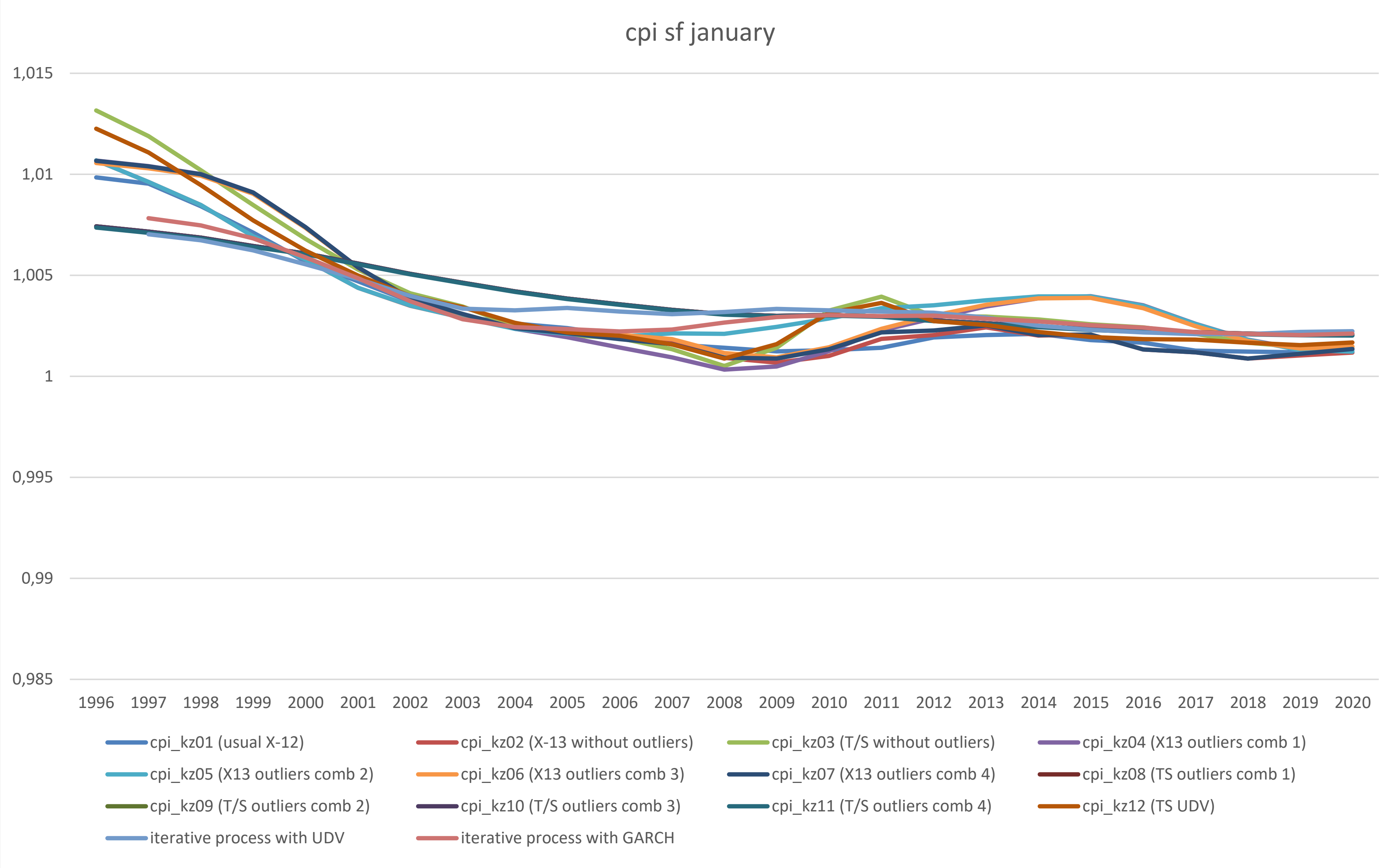
4. Tiller R.B., Evans T.D. (2017). Methodology for Seasonally Adjusting National Household Survey Labor Force Series with Revisions for 2017.

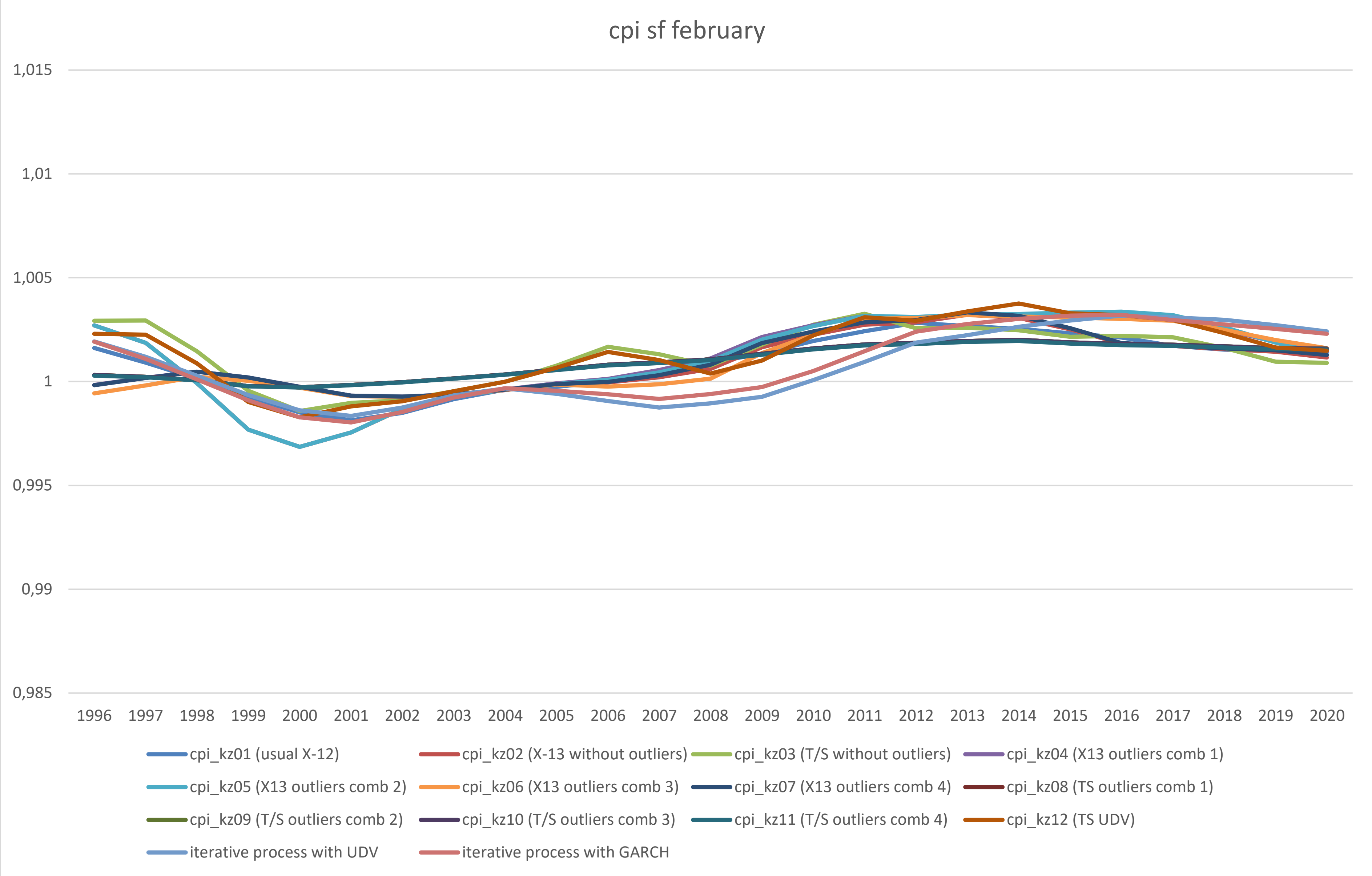
5. Maravall A., Gomez V. (1992). Signal Extraction in ARIMA Time Series – Program SEATS.

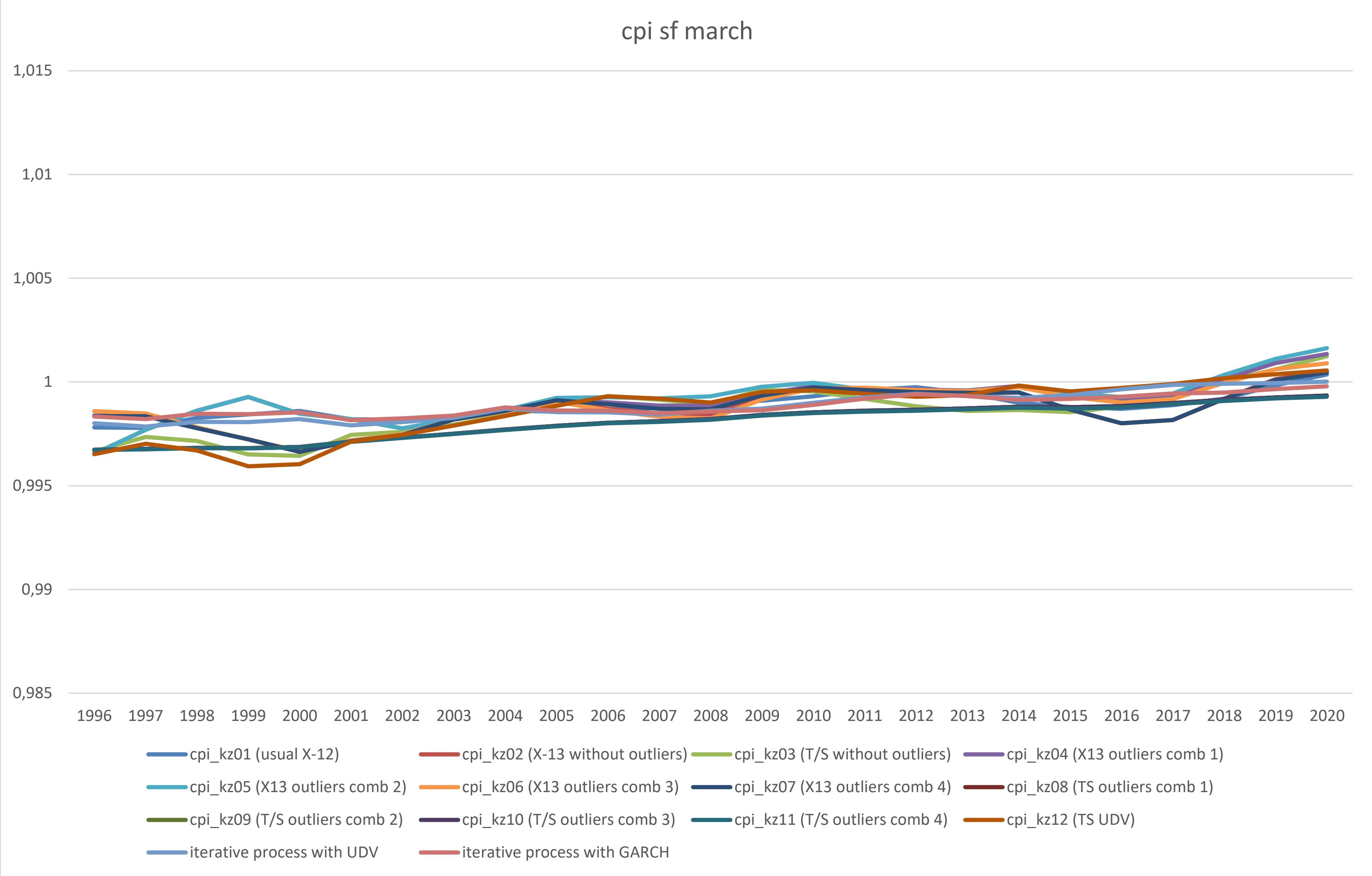
Appendix 1. Revision Error X-12-ARIMA (1 0 2)(1 0 1)

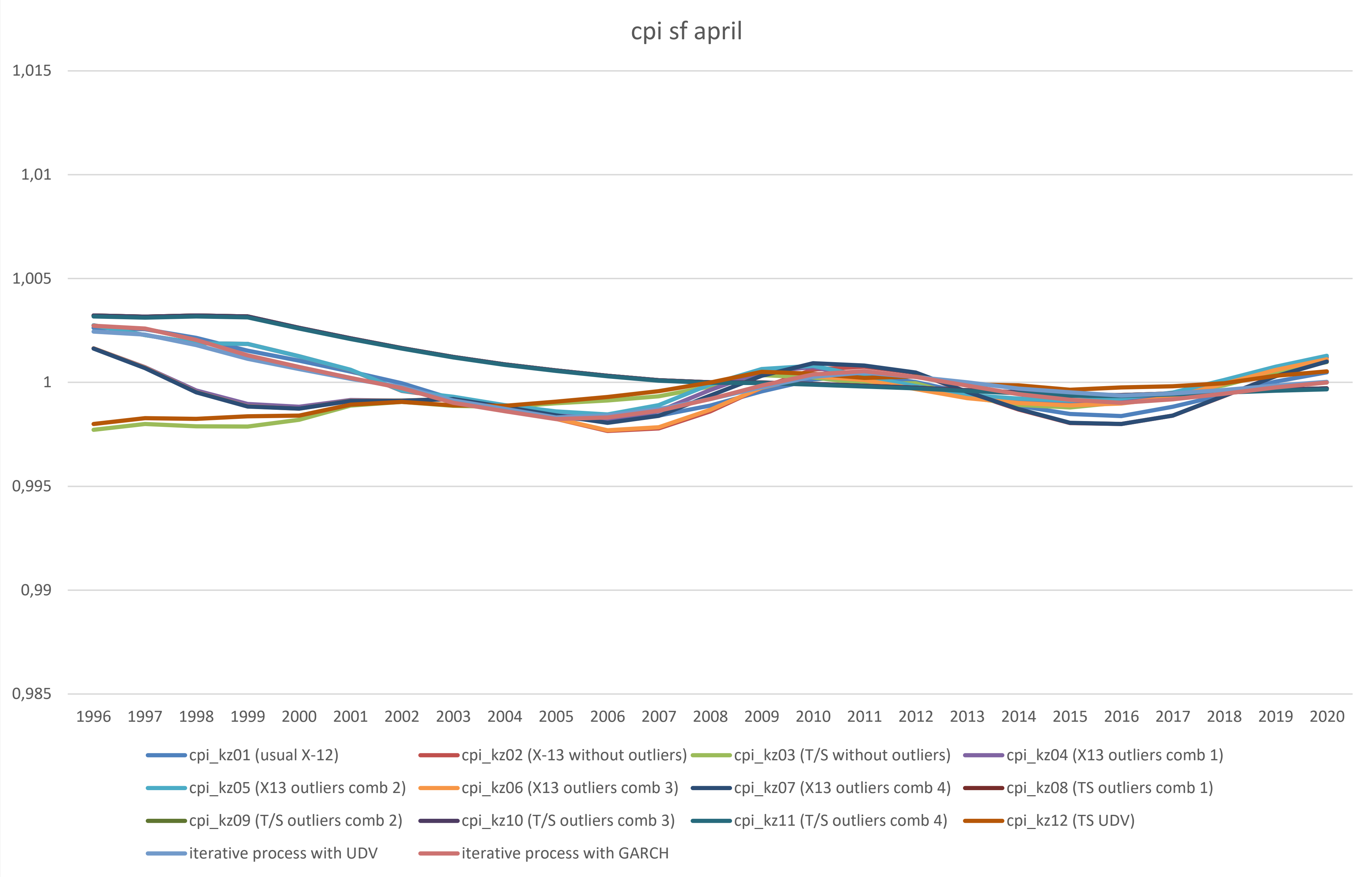


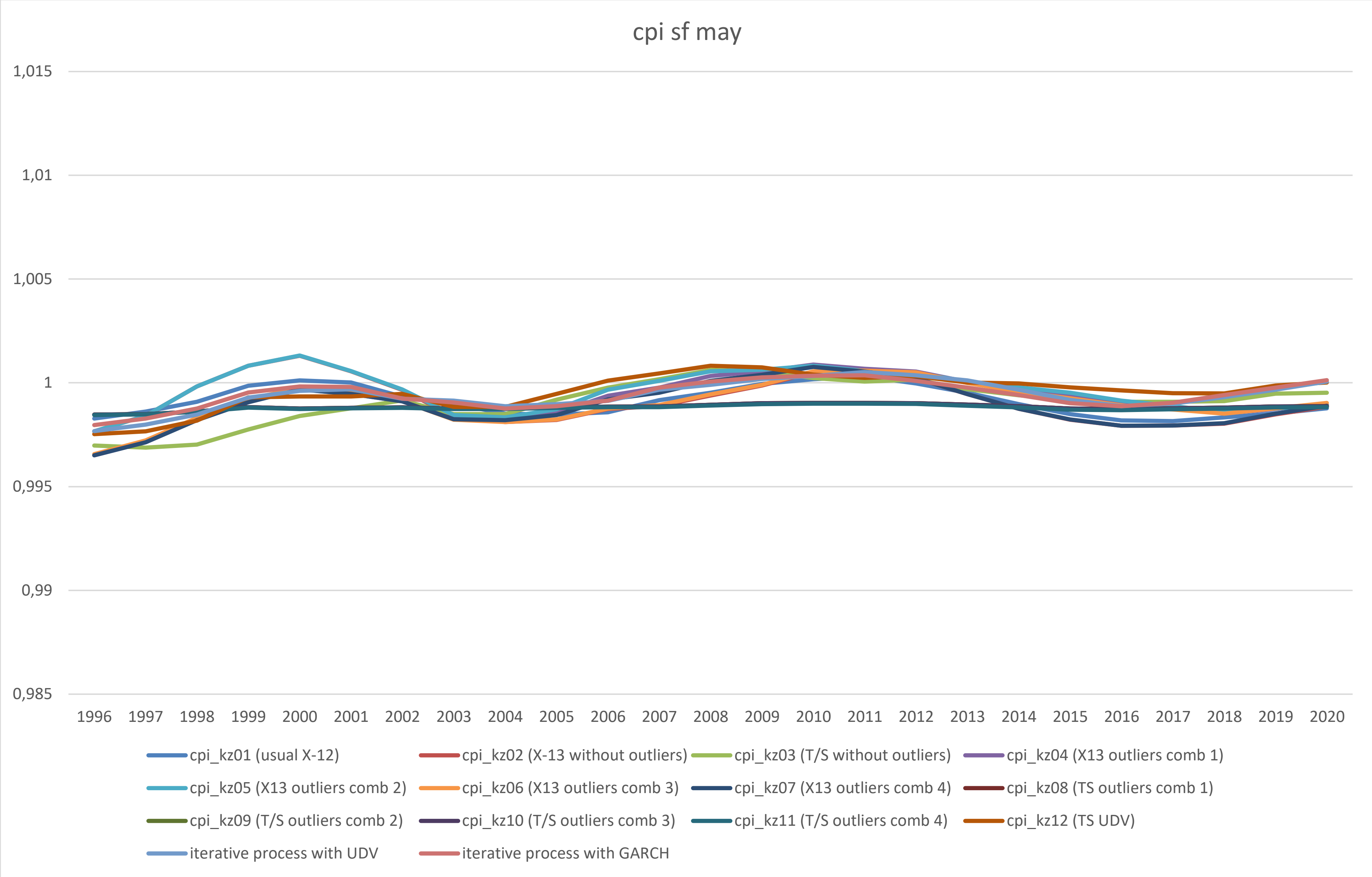
Appendix 2. Seasonal Factor Diagrams, by Months

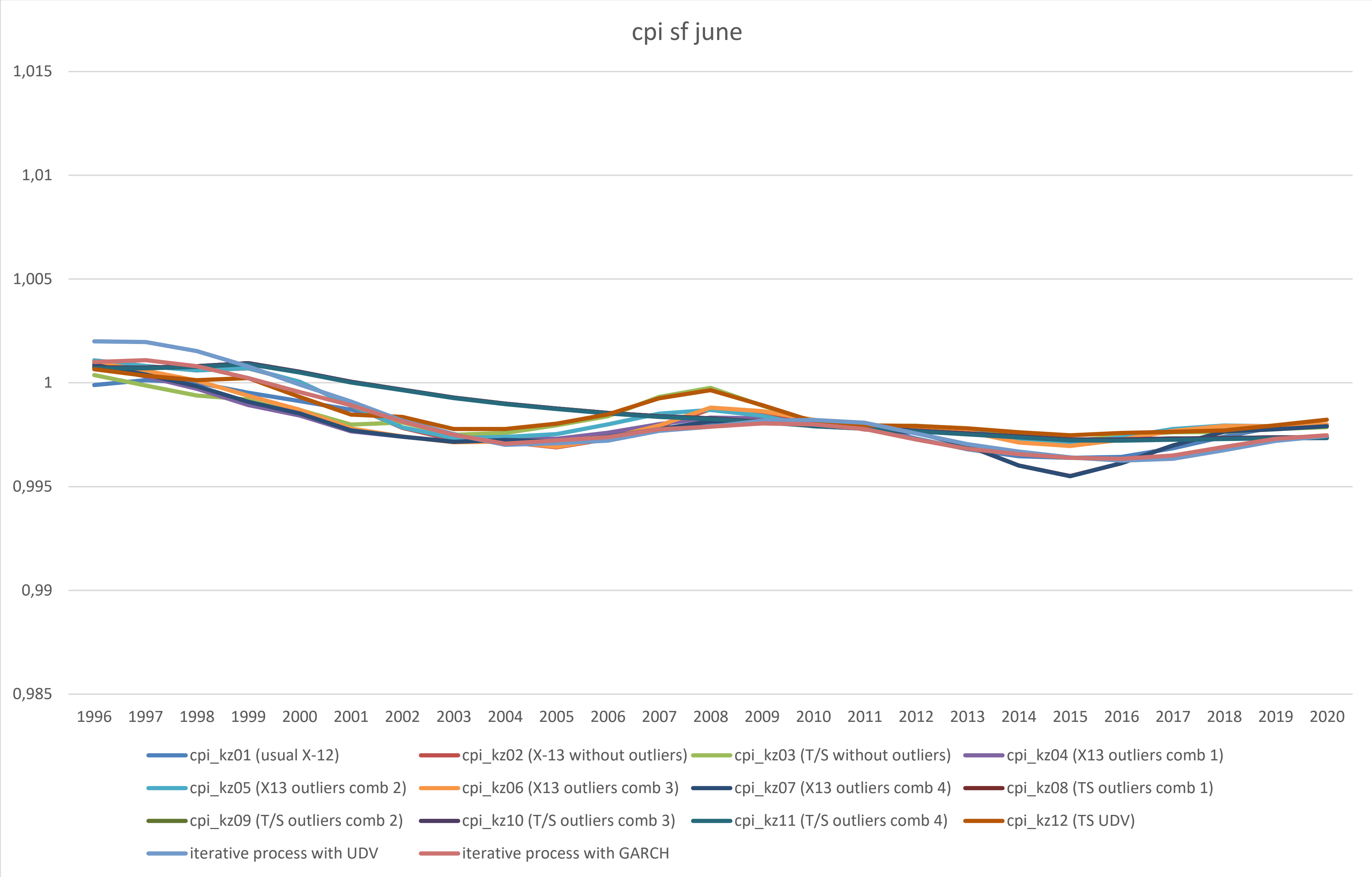


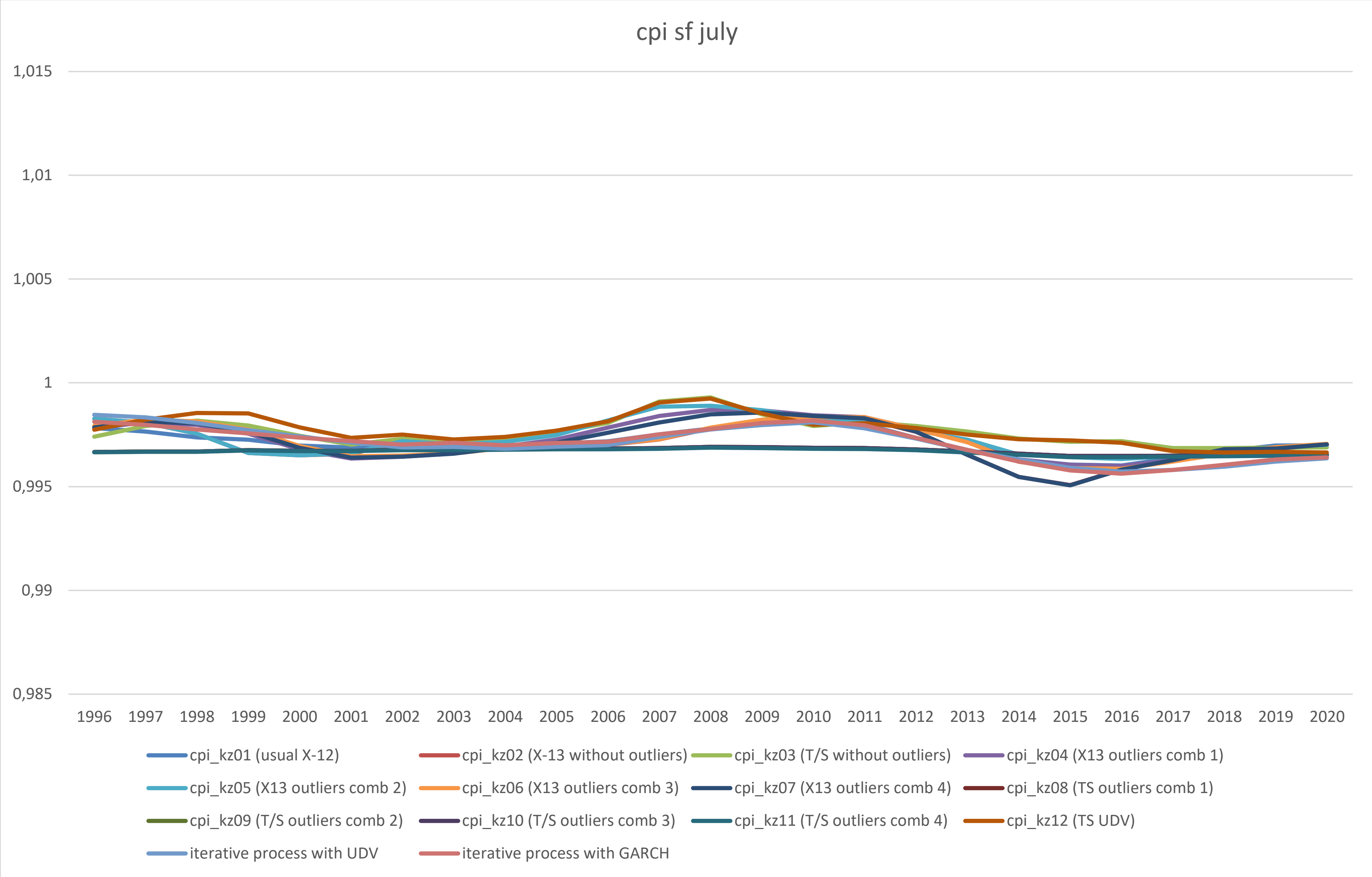

cpi sf february
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH

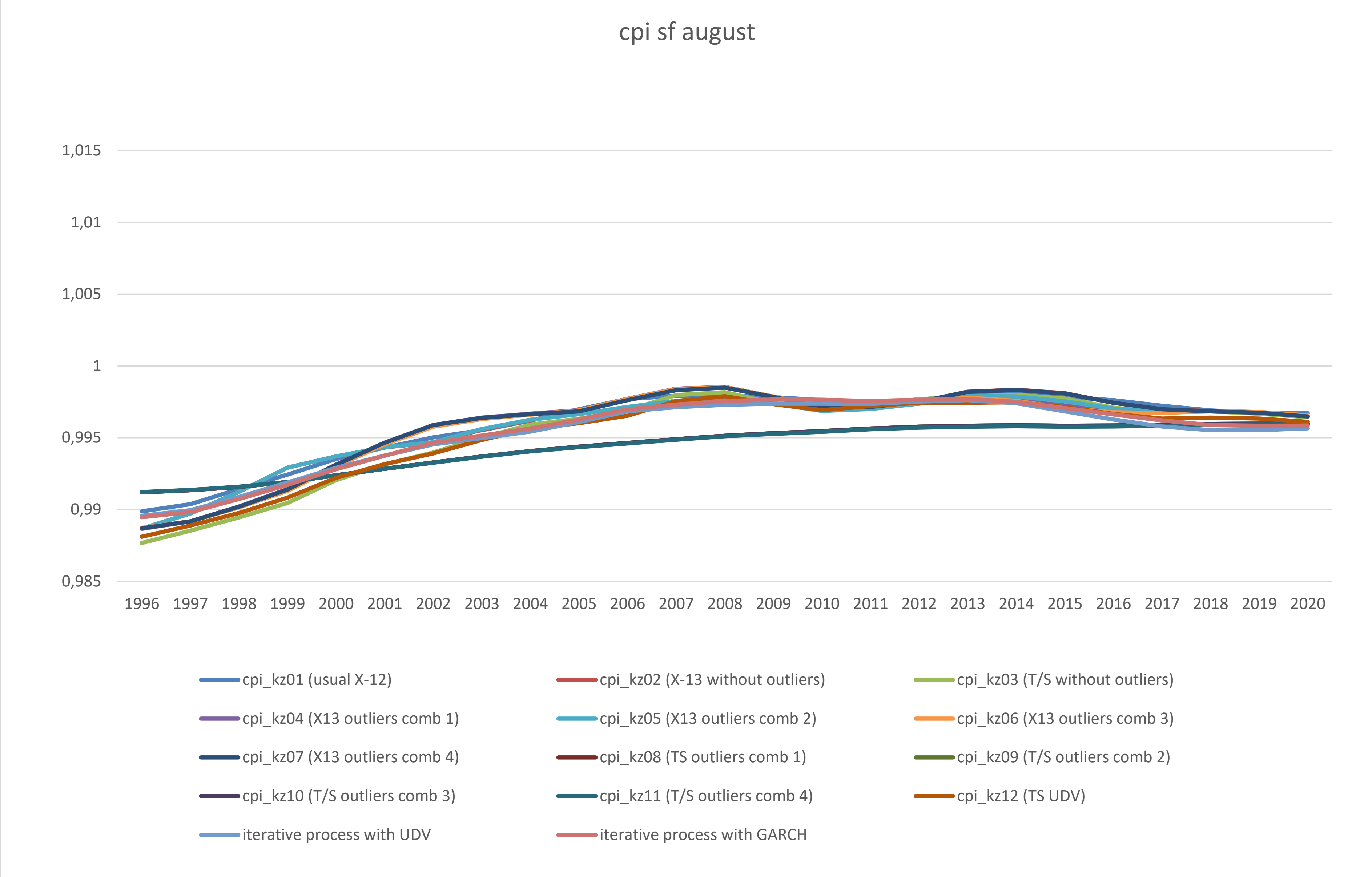

cpi sf march
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH

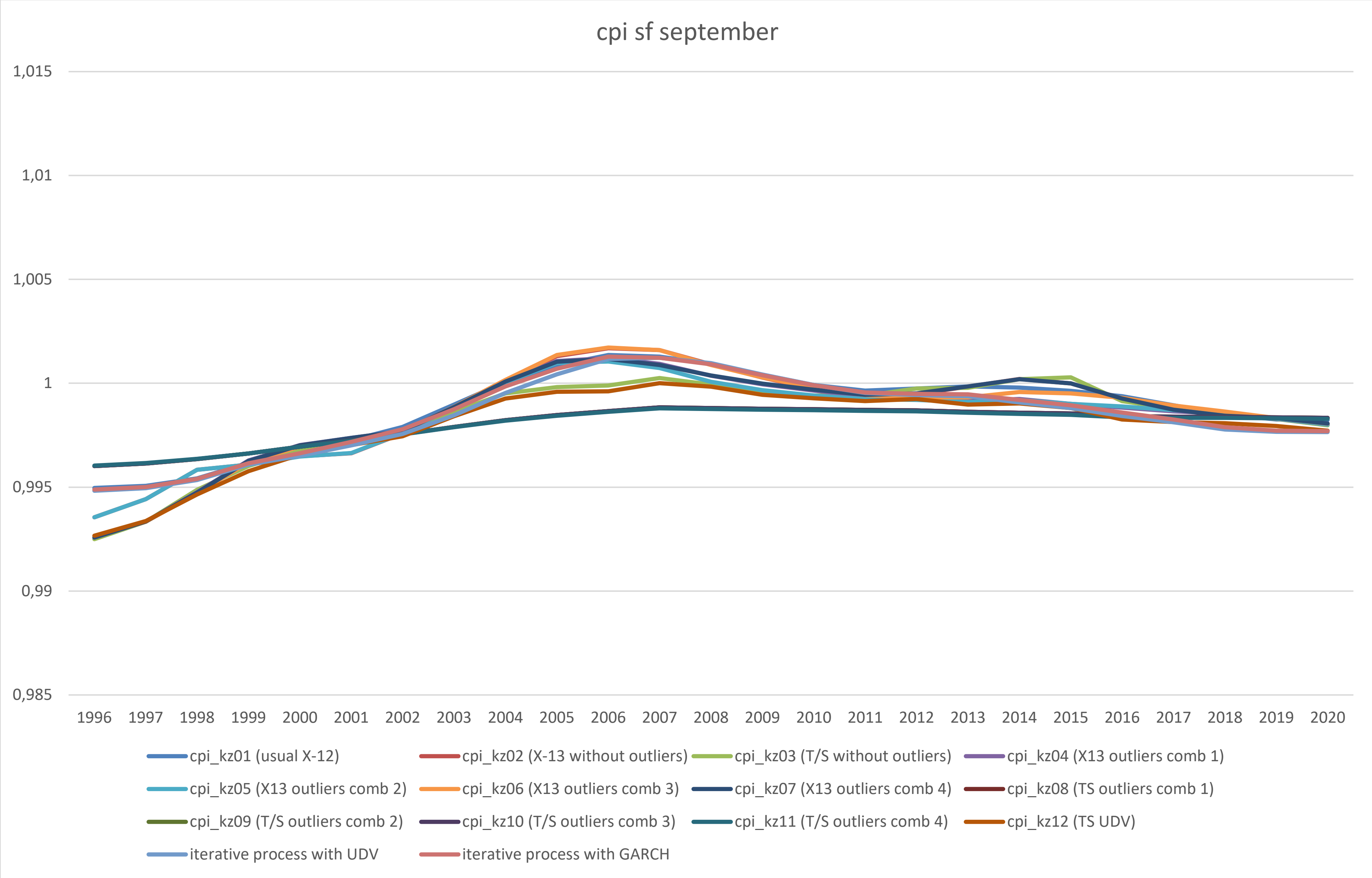

cpi sf april
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH

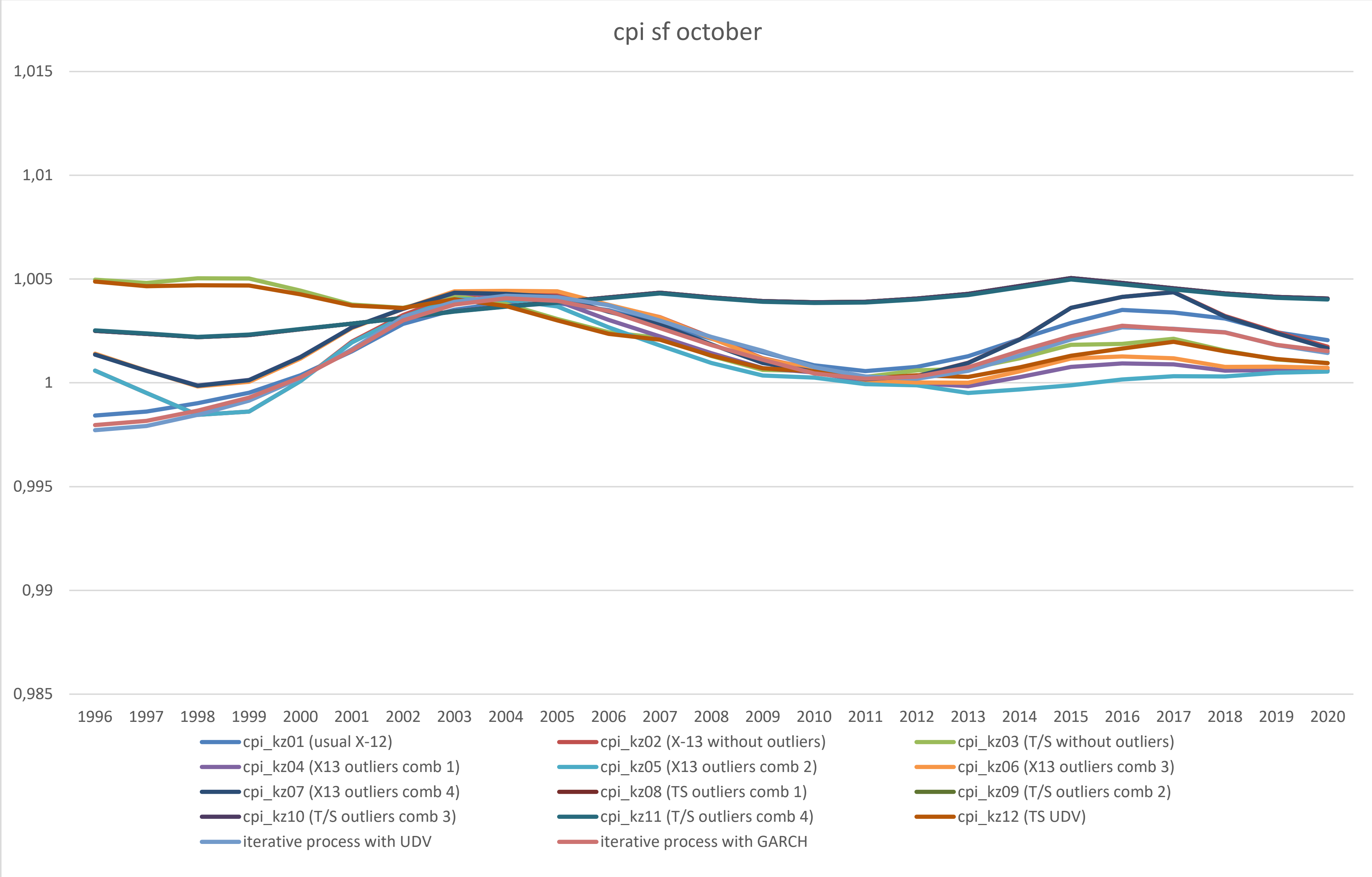

cpi sf may
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH

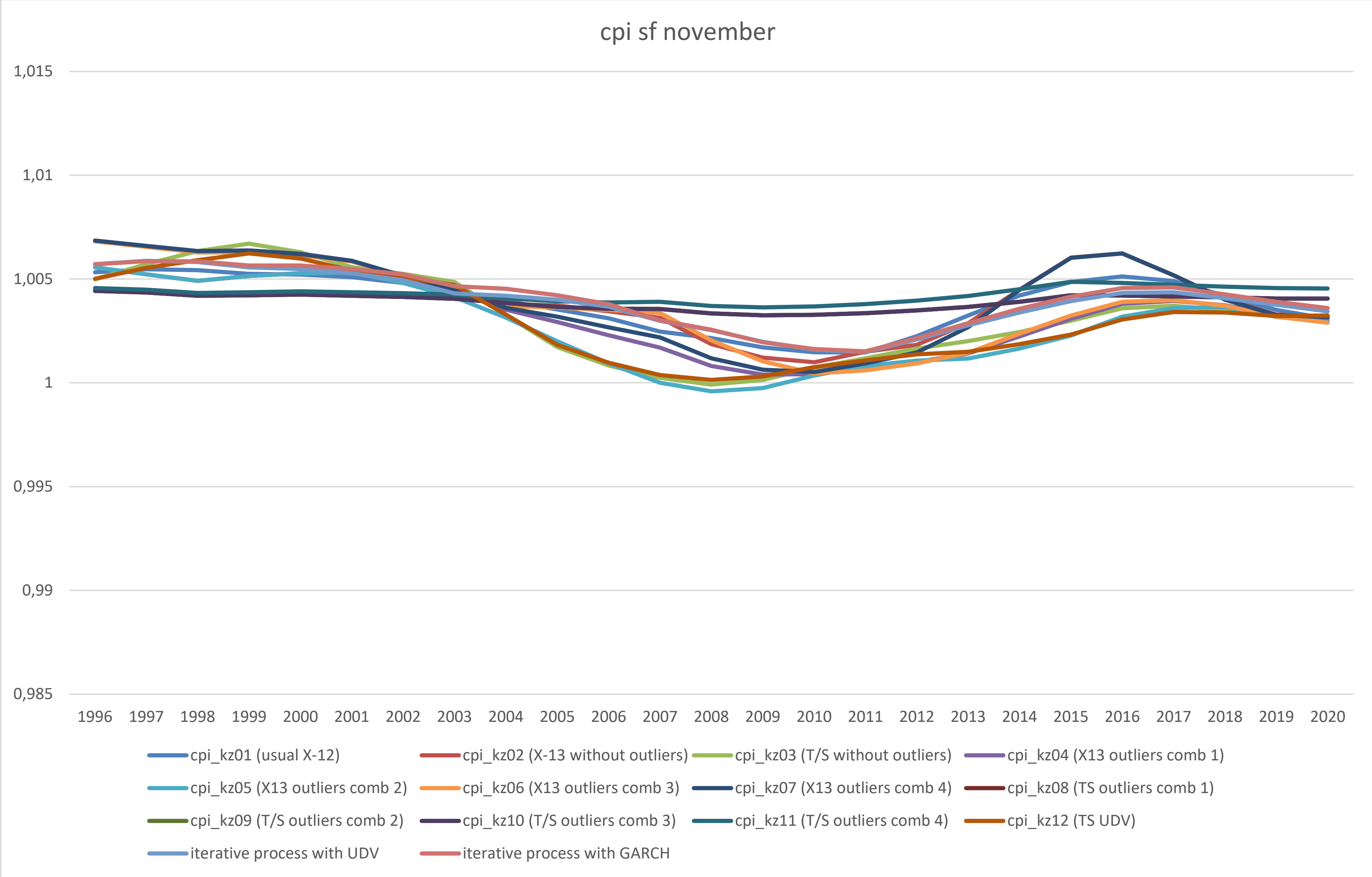

cpi sf june
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH

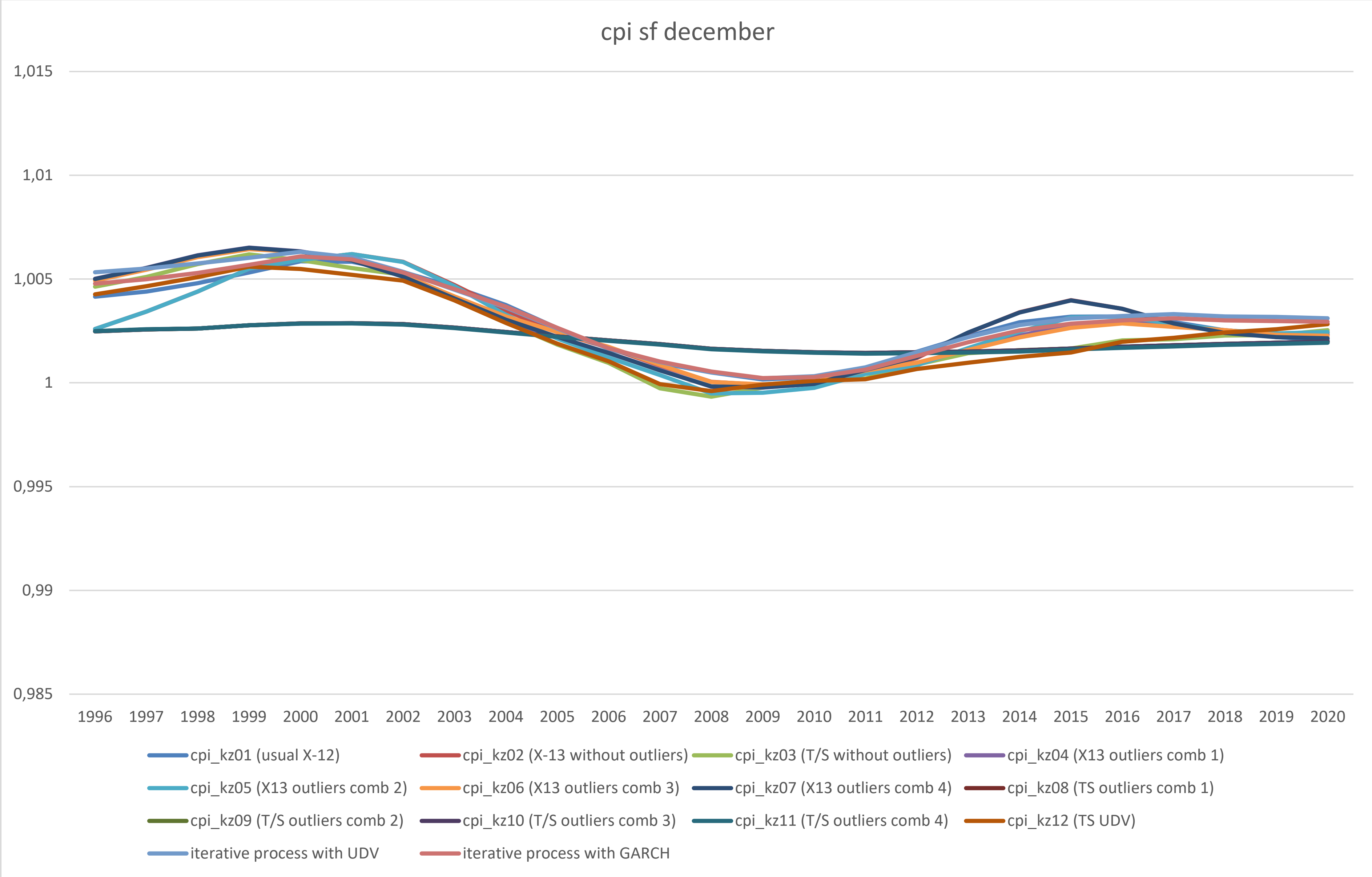

cpi sf july
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH


cpi sf august
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH

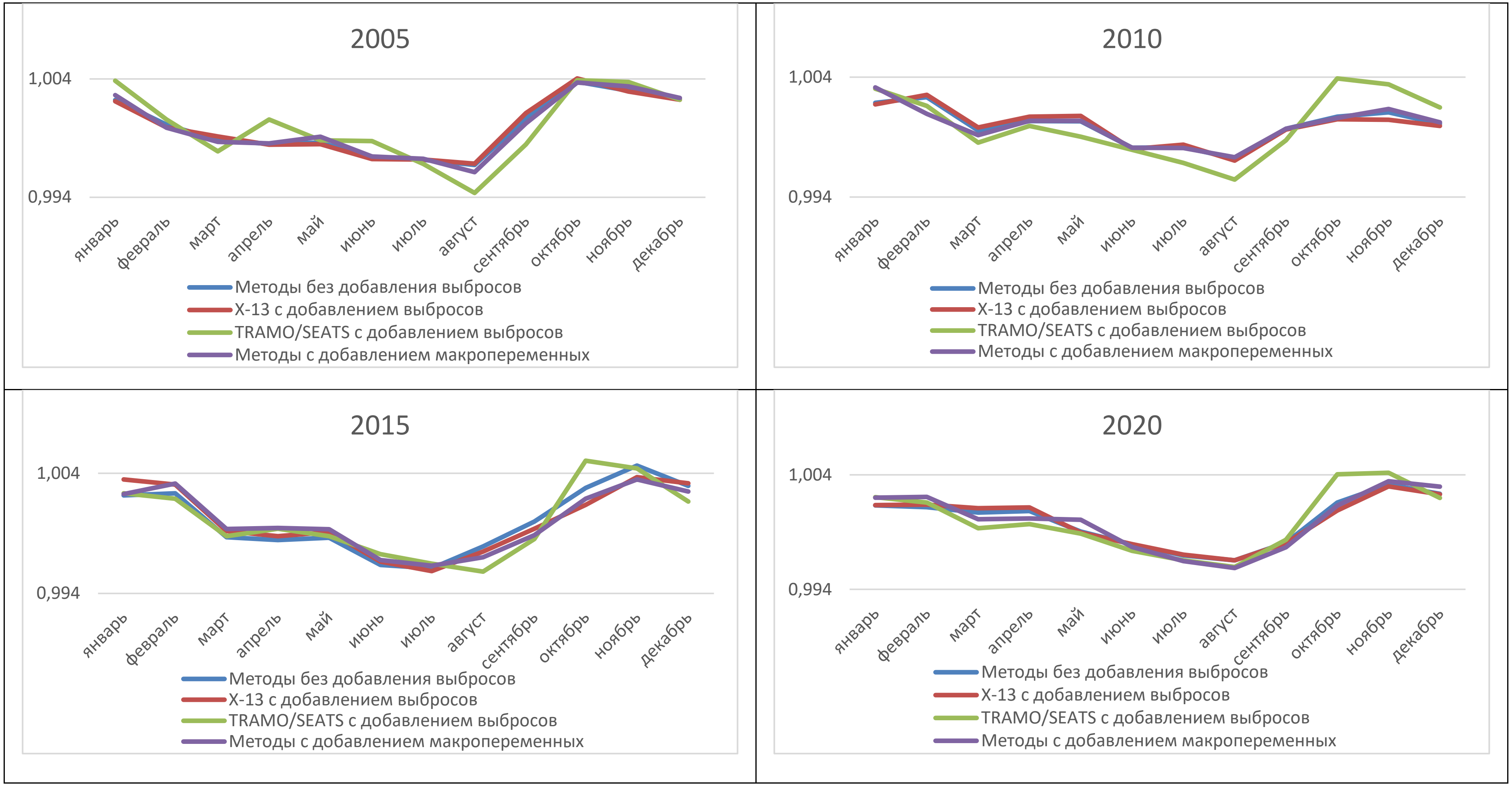

cpi sf september
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH


cpi sf october
1,015
1,01
1,005
1
0,995
0,99
0,985
1996
1997
1998
1999
2000
2001
2002
2003
2004
2005
2006
2007
2008
2009
2010
2011
2012
2013
2014
2015
2016
2017
2018
2019
2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH


cpi sf november
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH

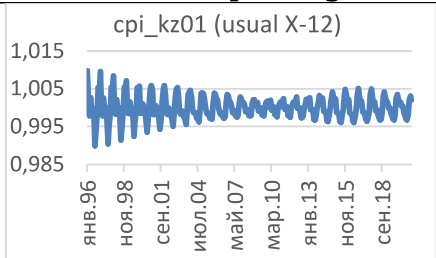

cpi sf december
1,015
1,01
1,005
1
0,995
0,99
0,985
1996 1997 1998 1999 2000 2001 2002 2003 2004 2005 2006 2007 2008 2009 2010 2011 2012 2013 2014 2015 2016 2017 2018 2019 2020
cpi_kz01 (usual X-12)
cpi_kz02 (X-13 without outliers)
cpi_kz03 (T/S without outliers)
cpi_kz04 (X13 outliers comb 1)
cpi_kz05 (X13 outliers comb 2)
cpi_kz06 (X13 outliers comb 3)
cpi_kz07 (X13 outliers comb 4)
cpi_kz08 (TS outliers comb 1)
cpi_kz09 (T/S outliers comb 2)
cpi_kz10 (T/S outliers comb 3)
cpi_kz11 (T/S outliers comb 4)
cpi_kz12 (TS UDV)
iterative process with UDV
iterative process with GARCH

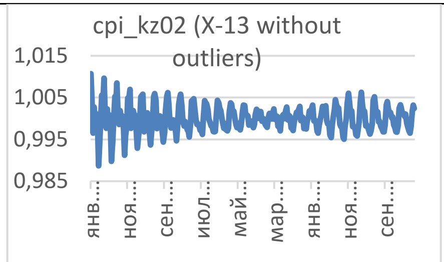
Appendix 3. Seasonal Pattern, by Years

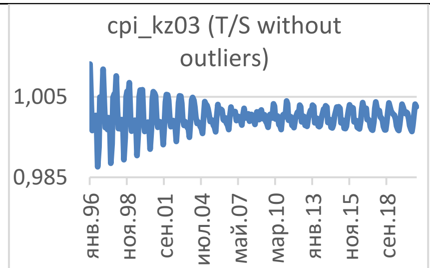


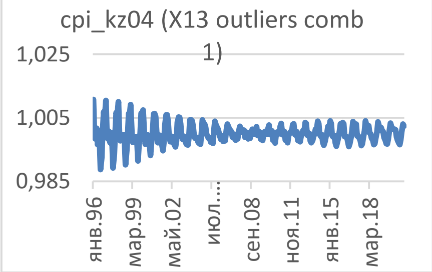
Methods without outliers; X-13 with outliers; TRAMO/SEATS with outliers; Methods with macro variables Jan; Feb; Mar; Apr; May; Jun; Jul; Aug; Sep; Oct; Nov; Dec

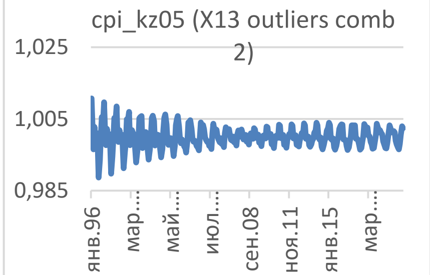
Appendix 4. Seasonal factors depending on the method

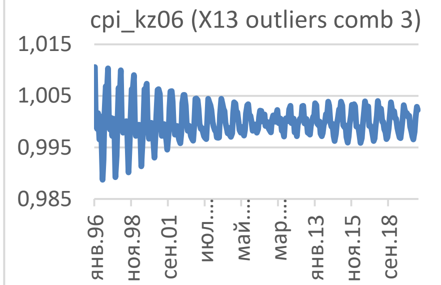
<table>
<tr>
<td>Methods without the addition of outliers</td>
<td>


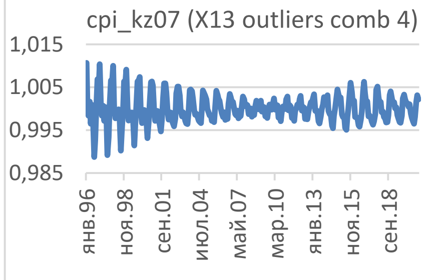
</td>
<td>


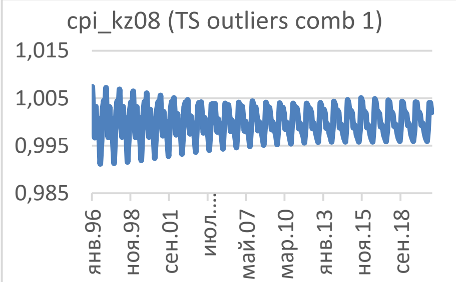
</td>
<td>


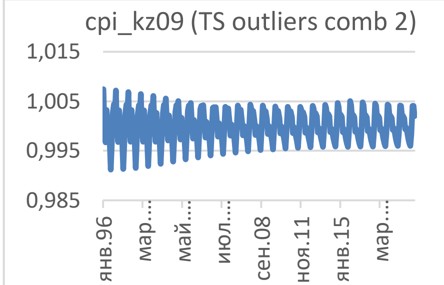
</td>
<td></td>
</tr>
<tr>
<td>X-13 with the addition of outliers</td>
<td>


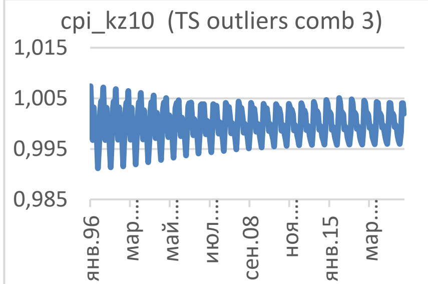
</td>
<td>


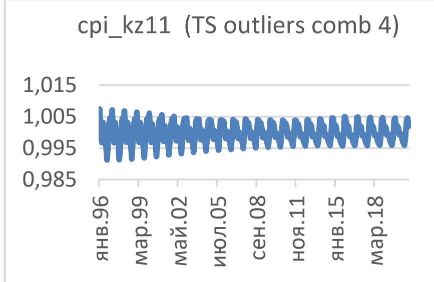
</td>
<td>


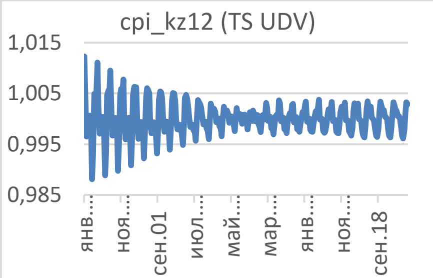
</td>
<td>


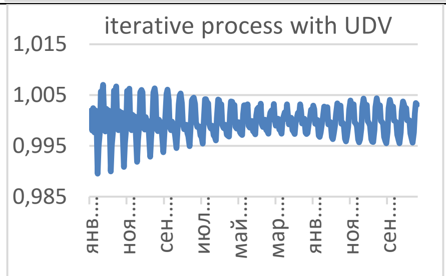
</td>
</tr>
<tr>
<td>TRAMO/SEATS with the addition of outliers</td>
<td>


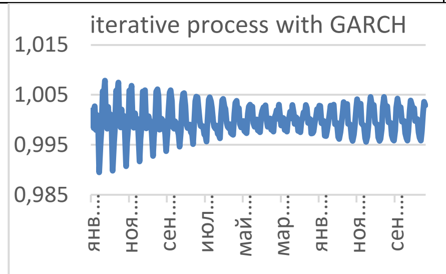
</td>
<td>


</td>
<td>


</td>
<td>


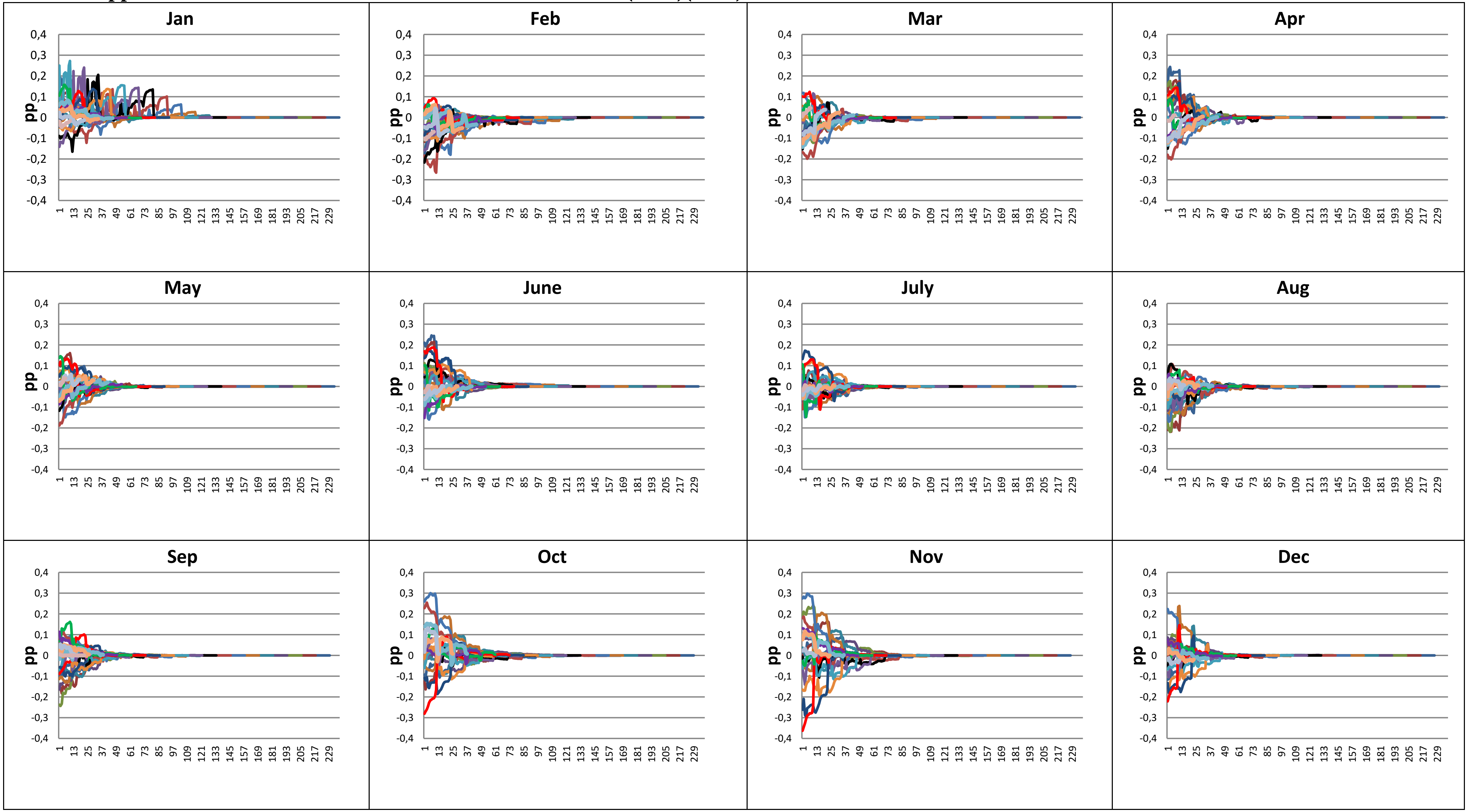
</td>
</tr>
<tr>
<td>Methods with the addition of macro variables</td>
<td>


</td>
<td>


</td>
<td>


</td>
<td></td>
</tr>
</table>

Appendix 5. Difference in the revision errors of ARIMA (1 0 2)(1 0 1)



THE MARKET OF CAR LOANS IN KAZAKHSTAN: OVERVIEW AND DEVELOPMENT PROSPECTS

Ismailov Amir – Chief Manager, Analytics Section, Risks and Analysis Division, "Kazakhstan Sustainability Fund" JSC.

This Paper is devoted to an overview of the current state of the car market in Kazakhstan through implementation of the Lending Program for Buyers of the Domestically Manufactured Cars.

Key Words: cars, motor vehicles, lending.
JEL Classification: G21, G68, H53, L62, R41, R42, R48.

1. The Current State of the Car Market in Kazakhstan

The presence of motor transport in Kazakhstan is one of the important components of the economy, an integral part of life of a modern person and an indicator of the material well-being of the population and society as a whole. In most countries of the world, an indicator such as the number of cars per 1,000 inhabitants is often used to characterize the level of development of motorization.

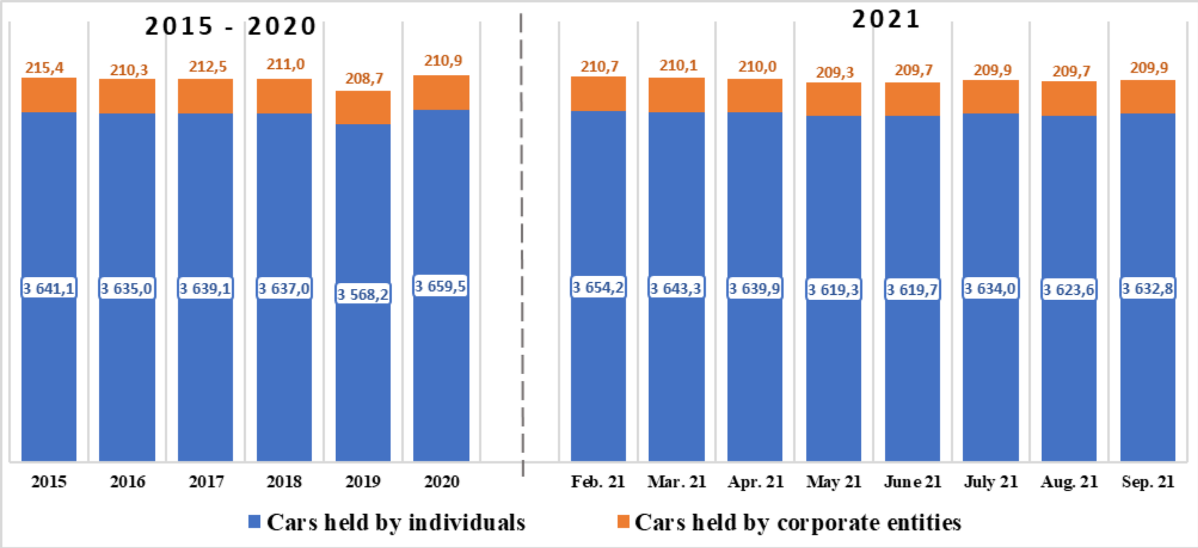
The level of motorization in developed countries is on average around 500-650 cars per 1,000 inhabitants, and in some countries this figure reaches 750 cars. For example, in the United States, the level of motorization is significantly higher than in the European Union countries, and the vehicle population is 828 on average across the country, and in metropolitan cities – a total of more than 900 cars per 1000 inhabitants. The level of motorization in Kazakhstan is 205 cars per 1,000 inhabitants.

For reference, the level of motorization in Russia was 309 cars per 1000 inhabitants, in Belarus – 334 cars, in Ukraine – 245 cars, in countries of Eastern Europe and Central Asia – in the range of 150-200 cars per 1000 inhabitants. Most developed countries have already passed the stage of "explosive" increase in the number of motor vehicles, which usually continues until it reaches 300 motor vehicles per 1,000 inhabitants, after which the growth rates of motorization slow down.

The state of the car market in Kazakhstan has remained relatively stable over the past few years. Thus, for example, in 2015, the number of available cars in Kazakhstan (*according to the Committee on Statistics of the Ministry of National Economy of the Republic of Kazakhstan*) was 3,856.5 thousand cars, while at the end of 2020 the fleet of cars exceeded 3,870.3 thousand (Fig. 1). During the period of 2015-2020, the actual number of motor vehicles did not change much, increasing a little over 0.3%. The "lion's share" in the car fleet belongs to the general public – more than 94.6% of the total number.

Figure 1

Availability of cars in Kazakhstan (in thousand)

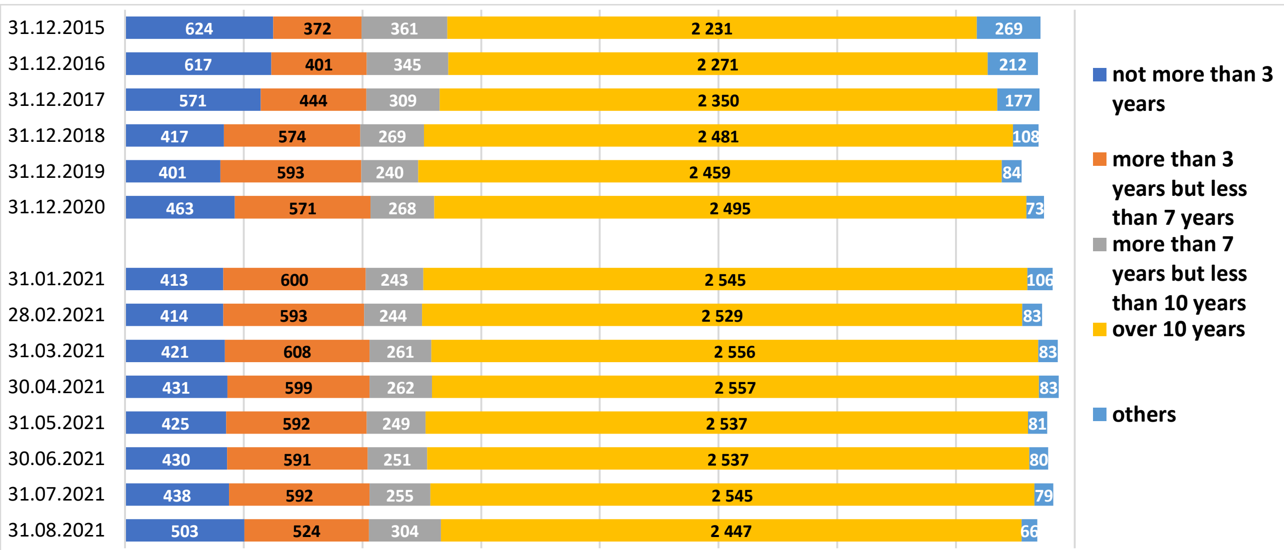


Source: Bureau of National Statistics of the ASPR RK

In recent years, due to the absence of a significant increase in the passenger car fleet, there has been a tendency of “ageing” of the car park in Kazakhstan (Fig. 2 and 3). Despite the growth of domestic manufacturing, measures initiated by the government for the purchase of old cars and the easing of conditions for the purchase of new cars under concessional programs, there is still an increased demand for used cars in Kazakhstan. So, at the end of 2015, the number of registered passenger cars over 7 years old was 67.2% of the total, and at the end of 2020 the share of such cars reached 71.4%.

Figure 2

Breakdown of cars in Kazakhstan by age (in thousand)



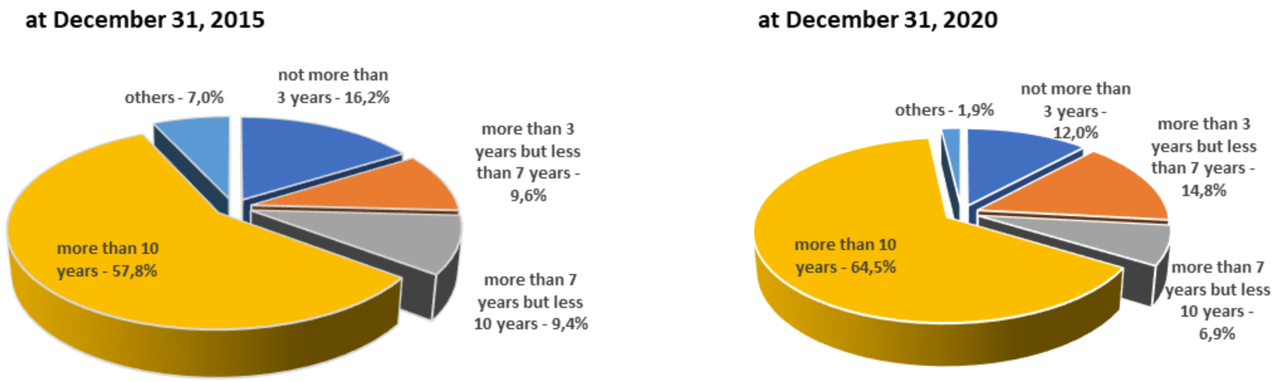
Source: Bureau of National Statistics of the ASPR RK

It is worth mentioning that, on the contrary, during the period from 2015 to 2020, the share of cars under 3 years decreased from 624 thousand to 463 thousand or from 16.2% to 12.0%, respectively. This also exacerbates the problem of car fleet ageing in Kazakhstan.

Geographically, the largest number of used cars over 7 years old is located in Almaty (10.7%) and Almaty region (14.9%). At the same time, the city of Almaty together with the city of Nur-Sultan are leaders in terms of the availability of cars under 3 years old.

Figure 3

The share of cars in Kazakhstan by age (as %)



Source: Bureau of National Statistics of the ASPR RK

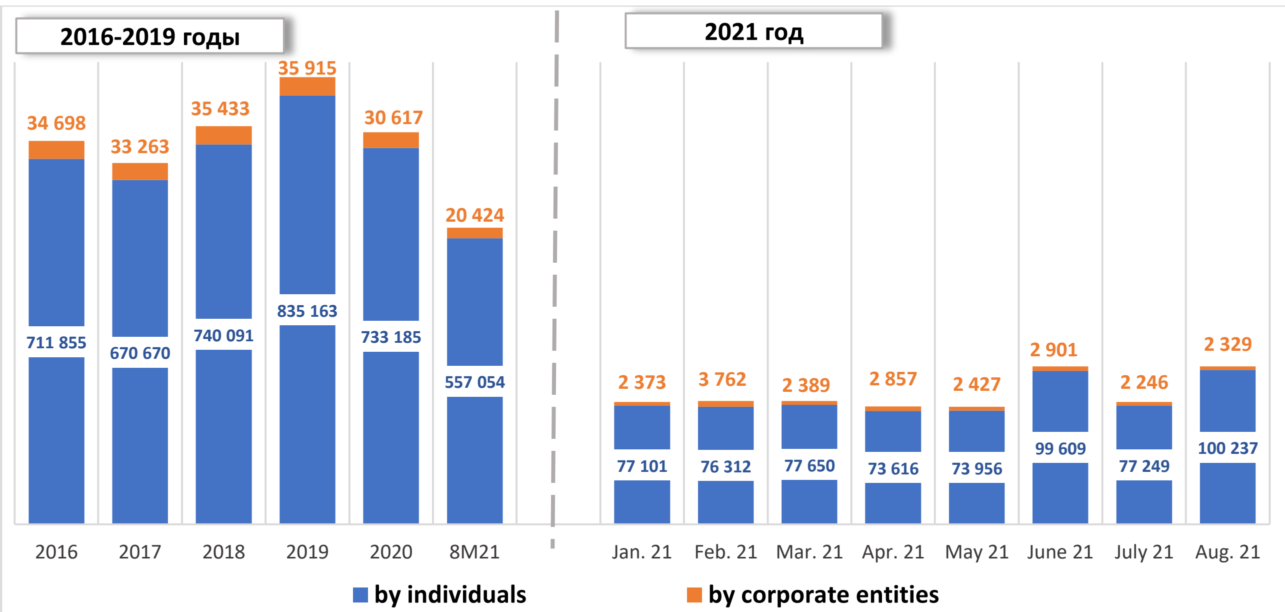
others; not more than 3 years; more than 3 years but less than 7 years; more than 7 years but less than 10 years; more than 10 years

Despite the absence of the growth dynamics in terms of the number of available car fleet, in 2020 more than 763 800 cars were registered in Kazakhstan, where the registration of cars by the population accounted for a major share – 96% of the total number (рис. 4). It is also worth mentioning that 66% of all cars registered in 2020 belonged to the category of more than 10 years old.

At the same time, according to the Bureau of National Statistics, during 8 months of 2021, the number of registered cars increased to 577 thousand. However, based on the data from the **Association of Kazakhstan Automobile Business (AKAB), approximately** 90% of registered cars are those from the secondary market.

Figure 4

The number of registered cars in Kazakhstan (in units)

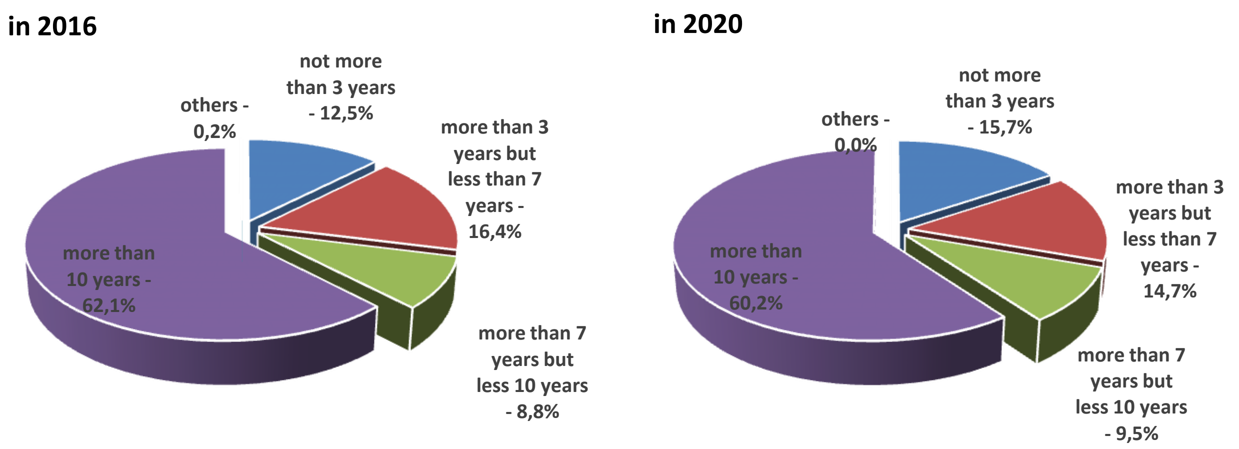


Source: Bureau of National Statistics of the ASPR RK

As for the breakdown by age categories, during the last year, cars with the useful life over 7 years account for a major share among registered cars; their percentage in 2020 reached 69.6% of the total number. At the same time, in 2020 the number of registrations of motor vehicles under 3 years accounted for 15.7% (рис. 5).

Figure 5

The share of registered cars by age in the period (in units)

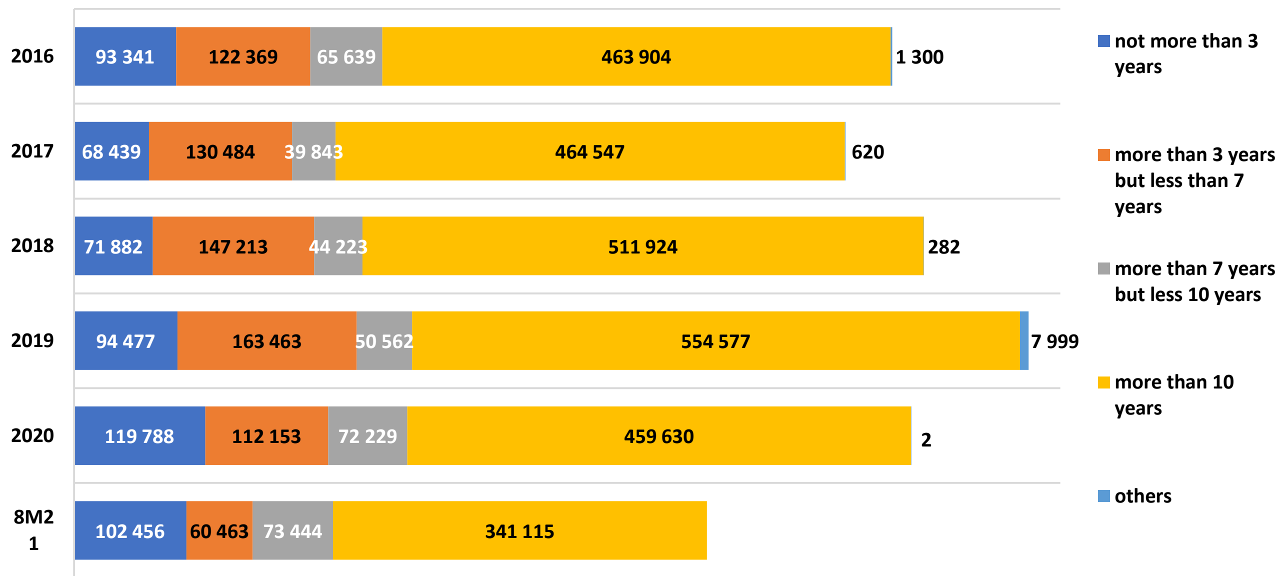


Source: Bureau of National Statistics of the ASPR RK

In quantitative terms, it can also be seen that the growth of car registrations in the period of 2015-2020 was secured by the re-registration of ownership of cars of an older year of manufacturing (Fig. 6). The five leaders in registration of used cars in 2020 were mainly the "southern" regions of Kazakhstan, such as: Almaty region (24.0%), Turkestan region (14.8%), Zhambyl region (10.8%), the cities of Almaty (16.0%) and Shymkent (10.0%).

Figure 6

The number of registered cars by age groups (in units)

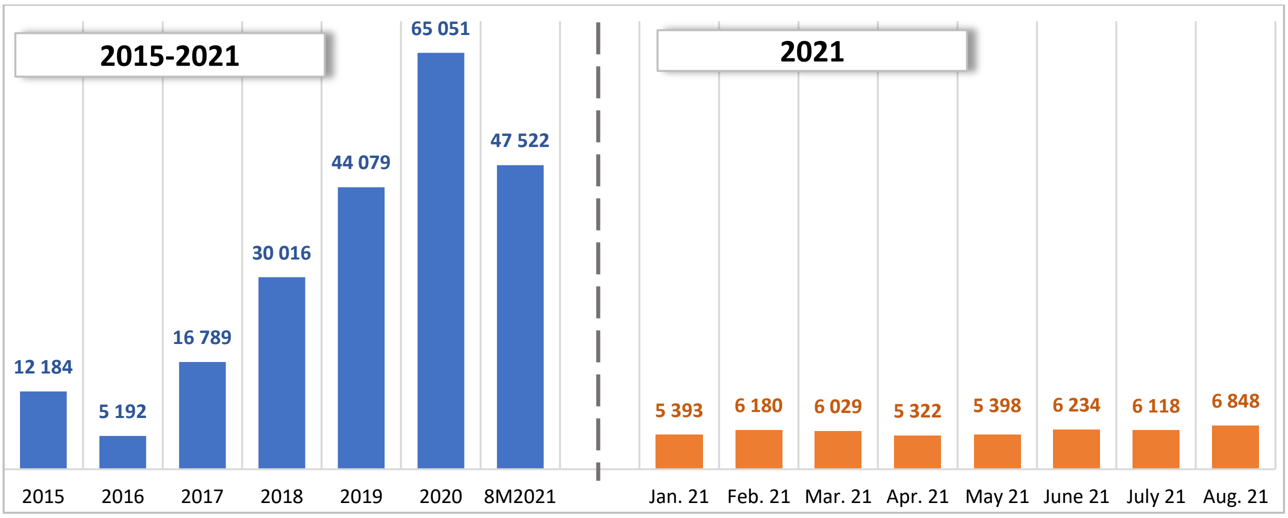


Source: Bureau of National Statistics of the ASPR RK

Although the actual number of cars has not undergone significant changes over the past five years, the domestic auto industry in recent years, after a decline in production in 2015-2016 and a drop in GDP in 2020, has shown a stable positive trend. Thus, the manufacturing of domestic cars in 2020 increased to 65,051 units against 5,192 units in 2016, showing a 12-fold increase. In 2021, the domestic car industry was able to continue the existing positive growth in the car manufacturing and assemble more than 47.5 thousand cars by the end of August (Fig. 7).

Figure 7

Domestic car manufacturing in 2015-2020 (in units)

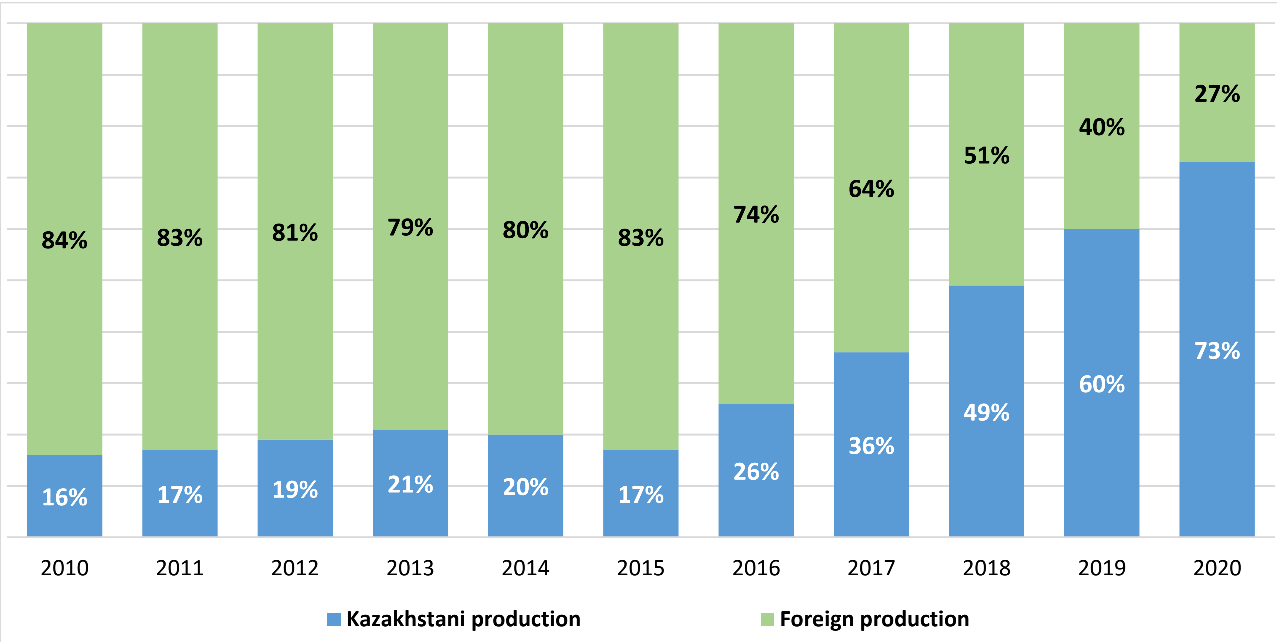


Source: Bureau of National Statistics of the ASPR RK

At the same time, with the growth in manufacturing of Kazakhstani cars, one can also observe a tendency towards import substitution of sales of new cars in car showrooms. Thus, the share of sales of Kazakhstani cars in 2020 reached 73%, having increased by 4.3 times compared to 2015 (Fig. 8).

Figure 8

Dynamics of growth in the percentage of car sales in car showrooms (in units)



Source: ***Association of Kazakhstan Automobile Business (AKAB) / Kazakhstani production; Foreign production***

The leaders in sales of the domestic car industry are cars of such brands as Hyundai, Chevrolet, Lada, Kia and JAC. Thanks to the restoration of Kazakhstani car manufacturing in 2020, two out of three sold cars were assembled in Kazakhstan, thus once again proving the long-term interest of car manufacturers and the government in developing the car industry.

2. Implementation of the Lending Program for Buyers of the Domestically Manufactured Cars

The government support of the domestic car industry is carried out through implementation of the Lending Program for Buyers of the Domestically Manufactured Cars ("the Car Loan Program"). The Car Loan Program has been implemented since 2015 by providing financing to the second-tier banks through the Car Loan Program operator – the "Development Bank of Kazakhstan" JSC and is designed for a period of 20 years. The main terms and conditions of the Program for obtaining a loan for the purchase of a car are as follows:

- nominal interest rate on the loan – not more than 4% per annum, annual effective interest rate should not exceed 7.5% per annum;
- loan tenor – not more than 7 years;
- loan currency – the tenge;
- the price of one car – not more than 15 million tenge;
- country of origin – manufactured in Kazakhstan.

From the time when the Car Loan Program was launched, the second-tier banks were provided financing through six separate tranches totaling 82 billion tenge. Specifically, two tranches were allocated in 2015-2016 from the National Fund of Kazakhstan amounting to a total of 26 billion tenge, two tranches were provided in 2018-2019 from the national budget and equaled 16 billion tenge and two more tranches were allocated in 2019-2020 for a total amount of 40 billion tenge through the National Bank of Kazakhstan.

Based on the revolving format of the Car Loan Program (*payments from repayment of existing loans are used again to disburse new loans*), at end-August 2021 the second-tier banks provided 28 476 loans totaling 145.7 billion tenge (Table 1).

Table 1

Actual uses of funds under the Car Loan Program as at 26.08.2021

Tranche No.	**Use of funds (mln tenge)**	**Actually disbursed loans**		
		Number	**Volume (mln tenge)**	**Percentage of use (%)**
Tranches 1 and 2	26 000	15 078	69 343	266.7%
Tranches 3 and 4	16 000	4 546	25 436	159.0%
Tranches 4 and 6	40 000	8 852	50 915	127.3%
Total:	**82 000**	**28 476**	**145 694**	**177.7%**

Source: "DBK" JSC

The allocated funds for purchasing the domestically manufactured cars were distributed among four major Kazakhstani car manufacturers:

- "Asia Auto" JSC;
- "Saryarka Avtoprom" LLP;
- "Agromachholding" JSC; and
- "Hyundai Trans Kazakhstan" LLP.

From the time when the Car Loan Program was launched in 2015, the distribution of the total volume of financing shows (Table 2) that the largest portion of sold cars was secured by "Asia

Auto" JSC and "Saryarka Avtoprom" LLP. The aggregate share of the two companies in the Program in 2021 accounted for 93.9% (Fig. 9).

Table 2

Uses of funds under the Car Loan Program among car manufacturers as at 26.08.2021

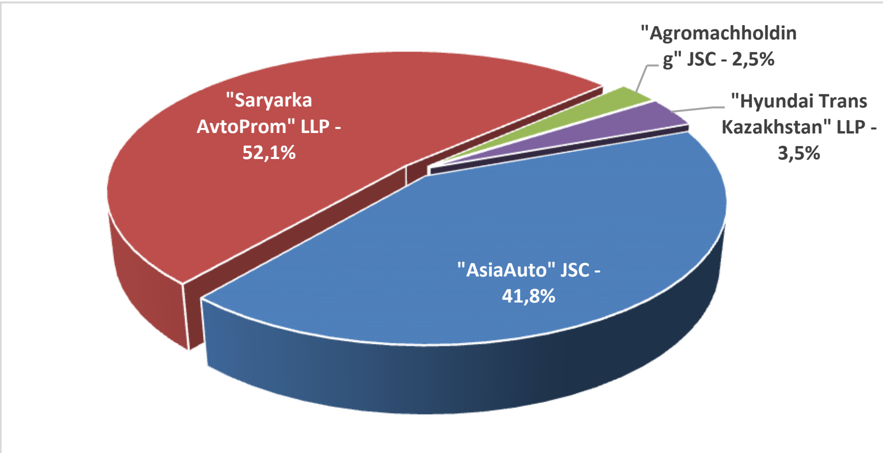
(mln tenge)

Manufacturer's Name	Tranche 1 and 2	Tranche 3 and 4	Tranche 5 and 6	Total
"Asia Auto" JSC	31 756	11 747	17 450	**60 953**
"Saryarka Avtoprom" LLP	33 706	13 646	28 578	**75 930**
"Agromachholding" JSC	3 689	-	-	**3 689**
"Hyundai Trans Kazakhstan" LLP	191	43	4 887	**5 121**

Source: "DBK" JSC

Figure 9

The share of Kazakhstani car manufacturers in the car loan program at 26.08.2021 (%)

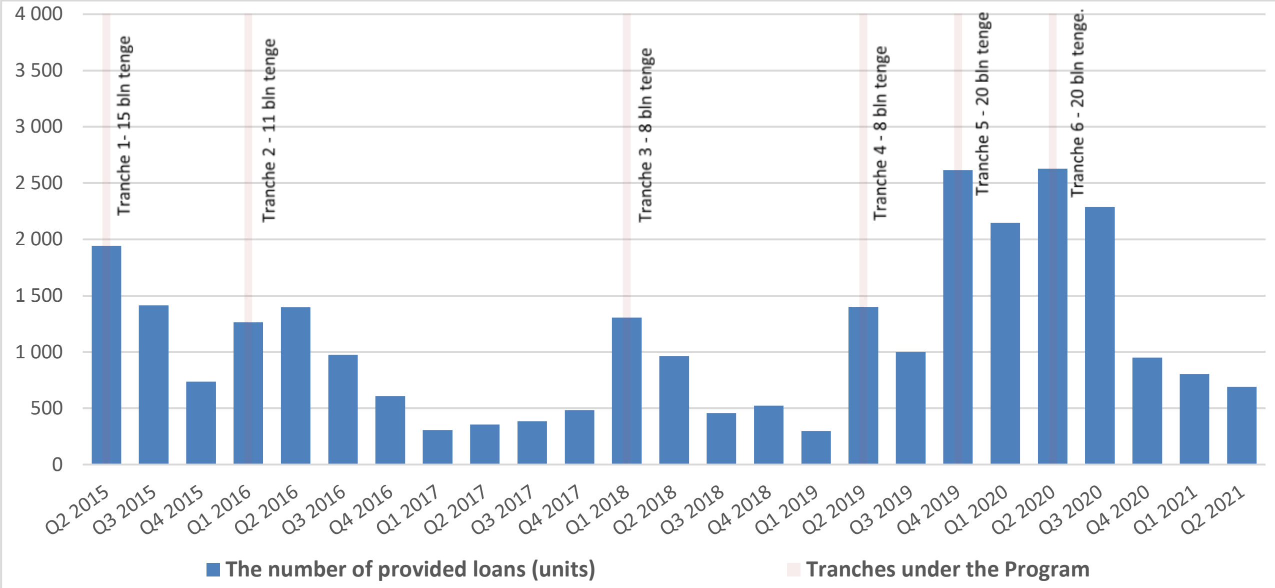


Source: "DBK" JSC

In general, the volume of loans provided by the second-tier banks for the purchase of domestically manufactured cars has a slightly cyclical curve and directly depends on the period when the Program Operator provides funds to the second-tier banks. By analyzing all car loans provided by banks from 2015 to 2020, one can observe the dependence of the growth in the number of made loans on the date and the amount of tranches provided under the Concessional Car Loan Program (Fig. 10). Thus, the constructed schedule of loans provided by banks for the purchase of cars shows the largest number of loans in the period of 2019-2020, when the total amount of funds allocated was 40 billion tenge. Also, the schedule of provided car loans shows an increase in volumes during the periods of the next tranches to the second-tier banks.

Figure 10

The number of car loans provided under the Program in 2015-2020 (in units)



Source: ***Association of Kazakhstan Automobile Business (AKAB)***

The number of provided loans (units); Tranches under the Program

According to the Association of **Kazakhstan Automobile Business,** 92 989 new cars and commercial vehicles were sold by Kazakhstani car dealers in 2020. Given the share of Kazakhstani content among new cars sold, the number of domestically manufactured cars reached almost 68 thousand. Since in 2020, the second-tier banks provided 8,012 loans under the Concessional Car Loan Program, it is worth mentioning that every 8th sold new domestically manufactured car was sold through the Program.

Thus, given a rapid disbursement by banks of funds allocated by the Operator and the demand among the population, one can note the positive and successful implementation of this Car Loan Program. Taking into account the repayment of previously provided car loans and the revolving format of the current Car Loan Program, it is worth mentioning that Kazakhstanis will still be able to continue to take concessional car loans on the same terms until the expiration of the program.

List of References:

1. Car Market in Kazakhstan: the 2020 Results in Numbers. https://akab.kz/avtorynok-rk-itogi-2020-goda-v-czifrah/.
2. The AKAB’s Bulletin for July 2021. https://akab.kz/wp-content/uploads/2021/08/vestnik-iyul-2021-goda.pdf.
3. The Status and the Development Path of Motor Transport in the Republic of Kazakhstan. https://applied-research.ru/ru/article/view?id=5628.
4. Motor vehicles per 1000 people: Countries Compared. https://www.nationmaster.com/country-info/stats/Transport/Road/Motor-vehicles-per-1000-people.
5. Passenger car rate. https://w3.unece.org/PXWeb/en/CountryRanking?IndicatorCode=44.
6. Press Releases of the Union of Automotive Industry in Kazakhstan. https://kazautoprom.kz/.
7. Statuses of Applications for Concessional Car Loans. https://kdb.kz/reporting-on-implementation-of-programmes/.
8. Lending Program for Buyers of the Domestically Manufactured Cars. https://online.zakon.kz/Document/?doc_id=35627502#pos=2;-83.