Statistiska centralbyrån Statistics Sweden

Consistent Seasonal Adjustment and Trend-cycle Estimation

2013:3

The series Background facts presents background material for statistics produced by the Department of Labour and Education Statistics at Statistics Sweden. Product descriptions, methodology reports and various statistic compilations are examples of background material that give an overview and facilitate the use of statistics.

Publications in the series
Background facts on Labour and Education Statistics

2000:1	Övergång till yrkeskodning på fyrsiffernivå (SSYK) och införande av jobbstatus-kod i SCB:s lönestatistik
2000:2	The Information System for Occupational Injuries and the Work-related Health Problems Survey – A comparative study
2000:3	Konferens om utbildningsstatistik den 23 mars 2000
2001:1	Avvikelser i lönesummestatistiken – en jämförelse mellan LAPS och LSUM
2001:2	En longitudinell databas kring utbildning, inkomst och sysselsättning 1990–1998
2001:3	Staff training costs 1994–1999
2001:4	Studieresultat i högskolan i form av avklarade poäng
2001:5	Urvals- och estimationsförfarandet i de svenska arbetskraftsundersökningarna (AKU)
2001:6	Svar, bortfall och representativitet i Arbetsmiljöundersökningen 1999
2001:7	Individ- och företagsbaserad sysselsättningsstatistik – en jämförelse mellan AKU och KS
2002:1	Tidsseriebrott i utbildningsregistret 2001-01-01
2002:2	En longitudinell databas kring utbildning, inkomst och sysselsättning (LOUISE) 1990–1999
2003:1	Exempel på hur EU:s ”Quality Reports” kan skrivas – avser Labour Cost Survey (LSC) 2000
2003:2	Förändrad redovisning av högskolans personal
2003:3	Individ- och företagsbaserad sysselsättningsstatistik – en fortsatt jämförelse mellan AKU och KS
2003:4	Sjukfrånvarande enligt SCB och sjukskrivna enligt RFV
2003:5	Informationssystemet om arbetsskador och undersökningen om arbetsorsakade besvär. En jämförande studie
2004:1	Samlad statistik från SCB avseende ohälsa
2004:2	Översyn av forskarutbildningsstatistiken. Bedömning av kvaliteten
2004.3	Sjukfrånvaro och ohälsa i Sverige – en belysning utifrån SCB:s statistik
2005:1	En longitudinell databas kring utbildning, inkomst och sysselsättning (LOUISE) 1990–2002
2005:2	Nordisk pendlingskarta. Huvudrapport
2005:3	Nordisk pendlingskarta. Delrapport 1–4.
2005:4	Flödesstatistik från AKU
2005:5	Flow statistics from the Swedish Labour Force Survey
2006:1	Sysselsättningsavgränsning i RAMS – Metodöversyn 2005

Continued on inside of the back cover!

Background Facts

Consistent Seasonal Adjustment and Trend-cycle Estimation

Labour and Education Statistics 2013:3

Statistics Sweden
2013

Background Facts

Labour and Education Statistics 2013:3

Consistent Seasonal Adjustment and Trend-cycle Estimation

Statistics Sweden
2013

Producer Statistics Sweden, Population and Welfare Department
BOX 24300
SE-104 51 STOCKHOLM

Inquires Daniel Samuelsson +46 8 506 949 78
daniel.samuelsson@scb.se

Elisabet Andersson +46 8 506 946 45
elisabet.andersson@scb.se

ISSN 1654-465X (Online)

URN:NBN:SE:SCB-2013-AM76BR1303_pdf

This publication is only available in electronic form on www.scb.se.

Preface

The Swedish Labour Force Survey (LFS) is a monthly, quarterly and annual survey. The quarterly and annual estimations are functions of the monthly data. Comparisons between adjacent months cannot be done based on the original series, as these contain a seasonal component. Therefore, developments on the labour market have traditionally been presented as the change between the current month or quarter and the same period in the previous year. The drawback of this method of presenting a change in the labour market is that it does not show when it took place; and furthermore, changes in the labour market or the business cycle are detected with several months' delay. The most important users of the LFS statistics are the Ministry of Finance, Ministry of Employment, National Institute of Economic Research, Riksbank, Eurostat, etc., which have therefore seasonally adjusted the LFS data series themselves.

During 2009, Statistics Sweden started developing a system for time series analysis and seasonal adjustment of the LFS data series. The first module in the system was implemented in production in early 2010. Today, the system handles about 4 000 original series. The seasonal adjustment is done using X12- ARIMA so that the seasonally adjusted series and the trend series are correspondingly consistent with the original series.

This work has been conducted in association with the most important users of the LFS data. Anders Wallgren and Britt Wallgren have been responsible for the methodological work and are the authors of this report. Within the framework of this project, they have developed a unique method to achieve consistency within a system of series, which is requested by many users.

We hope that the report will give users of the LFS data insight and knowledge about the system, and that the developed methods will contribute to the further development of the seasonal adjustment methodology.

Statistics Sweden, April 2013

Inger Eklund

Hassan Mirza

Contents

1 The changes in 2005 and 2007

During April 2005, a new questionnaire was introduced in the Swedish Labour Force Survey. The intention was to harmonise measurement methods with the standard used within the European Union. All labour status categories were affected by the change. As a result, comparing data produced with the old and new measurement methods became difficult and Statistics Sweden decided to postpone publication of seasonally adjusted values until linked time series had been derived.

Statistics Sweden subsequently stopped publishing seasonally adjusted LFS series. Different users including Eurostat started to produce their own seasonally adjusted data. As a consequence, there were different, parallel descriptions of the Swedish labour market.

1.1 User demands

The Swedish Labour Force Survey plays a very important role in Sweden. It is used by many analysts in the central government. Since different analysts can use different variables, the number of time series that are important is very large. These users requested thousands of long monthly and quarterly time series extending at least from 1987 and onwards.

For some years, Statistics Sweden and users within the central government had discussed the consistency of seasonally adjusted values. The quarterly National Accounts had generated the following inconsistent results, where seasonally adjusted values for the last two quarters were compared:

Imports of goods and services:	+1.3 %
Imports of goods:	+0.5 %
Imports of services:	–2.2 %

These kinds of estimates are difficult to interpret, and users need consistent seasonally adjusted values for their work with models and forecasts. Statistics Sweden has now changed its policy regarding seasonal adjustment – if possible, consistent adjustments should be produced.

1.2 Our aim

The manager of the Labour Force Survey assigned us the following task:

Develop methods for time series analysis that will produce consistent seasonally adjusted values and estimated trend-cycle values for a large number of specified monthly and quarterly series. Consistent calendar corrections should also be included in this methodology.

1.3 Project results

In February 2010, linked times series were published for the period January 1987 – March 2005. At the same time, consistent seasonally adjusted values and estimated trend values for a system of 480 monthly LFS series were published. Since then, an increasing number of seasonally adjusted series have been published and now about 1 250 monthly series are entered into the system. This input, consisting of series with number of persons, is used to generate corresponding series with percentages of the population or the labour force. The system also handles series describing numbers of hours actually worked. These monthly series are used to generate the corresponding quarterly series. All in all, about 4 000 series are seasonally adjusted – 2 000 monthly series and 2 000 quarterly series. Gradually, more and more of these series will be published.

1.4 Methodological issues

Multidimensional frequency tables give rise to systems of time series that are additive in many dimensions. LFS data are of this kind and there is a demand for adjusted values that are consistent in at least three dimensions.

How can we obtain consistent seasonally adjusted values and estimated trend values in such systems of series? This is the main issue that we discuss in this paper. How to correct for outliers? How to handle variation regarding measurement periods? How to adjust for calendar variation? These issues must also be incorporated in the developed methods to produce consistent series.

How to avoid mistakes when a small number of staff must handle a very large number of time series and publish seasonally adjusted values and estimated trends when pressed for time in their work? Finally, how should a large number of seasonally adjusted series and estimated trends be presented to users?

2 The structure of LFS data

Each month, about 15 000 time series are published in an Internet publication with about 40 Excel tables. The first of these tables is shown below. That chart contains 378 time series, with series describing absolute frequencies in thousands of persons and series describing relative frequencies in per cent. The same kind of tables is also published for quarterly and yearly data. Chart 1 is a three-dimensional frequency table that is additive in three dimensions, i.e. sex, age groups and labour status. In addition, there is consistency between absolute and relative frequencies and between monthly, quarterly and yearly data.

Chart 1. Labour force participation of the population by sex and age. LFS for August 2012

15-74 years in thousands								Unem-	Labour	Employ-
	POPULATION IN THE LABOUR FORCE					Persons	Population	ployment	force	ment
Sex	Employed			Unem-	Total	not in the	total	ratio	ratio	ratio
		Persons	Persons	ployed	Persons	labour	(6)+(7)	(4)	(6)	(1)
Age		at work	absent		in the	force		per cent	per cent	per cent
			from work		labour force			of (6)	of (8)	of (8)
	(1)	(2)	(3)	(4)	(6)	(7)	(8)	(9)	(10)	(11)
Both sexes										
15-24 years	526.3	448.1	78.2	139.3	665.7	567.2	1 232.9	20.9	54.0	42.7
25-34	975.2	683.7	291.5	81.3	1 056.5	135.7	1 192.2	7.7	88.6	81.8
35-44	1 122.2	739.4	382.8	56.1	1 178.3	82.5	1 260.8	4.8	93.5	89.0
45-54	1 086.5	771.3	315.3	57.7	1 144.3	117.3	1 261.6	5.0	90.7	86.1
55-64	866.3	605.7	260.7	40.0	906.3	256.7	1 163.0	4.4	77.9	74.5
65-74	141.2	104.7	36.5	..	148.2	861.2	1 009.4	..	14.7	14.0
15-74	**4 717.8**	**3 352.8**	**1 365.0**	**381.4**	**5 099.2**	**2 020.6**	**7 119.9**	**7.5**	**71.6**	**66.3**
of which										
15-19	121.7	110.1	11.7	50.6	172.3	399.1	571.4	29.4	30.2	21.3
20-24	404.6	338.0	66.5	88.7	493.3	168.1	661.5	18.0	74.6	61.2
16-64	4 571.1	3 243.7	1 327.4	372.1	4 943.2	1 066.7	6 009.9	7.5	82.3	76.1
20-64	4 454.9	3 138.1	1 316.8	323.8	4 778.7	760.3	5 539.0	6.8	86.3	80.4
Men										
15-24 years	269.9	228.3	41.7	74.4	344.4	288.4	632.8	21.6	54.4	42.7
25-34	520.4	380.5	139.8	44.0	564.4	45.8	610.2	7.8	92.5	85.3
35-44	585.4	401.3	184.1	30.7	616.1	24.1	640.2	5.0	96.2	91.4
45-54	562.8	412.3	150.4	32.5	595.3	45.0	640.3	5.5	93.0	87.9
55-64	463.4	333.8	129.6	21.4	484.8	97.2	582.0	4.4	83.3	79.6
65-74	89.8	64.4	25.5	..	94.8	401.5	496.4	..	19.1	18.1
15-74	**2 491.8**	**1 820.6**	**671.1**	**208.0**	**2 699.8**	**902.1**	**3 601.9**	**7.7**	**75.0**	**69.2**
of which										
15-19	58.9	53.6	5.3	23.8	82.7	211.5	294.2	28.8	28.1	20.0
20-24	211.1	174.7	36.4	50.6	261.7	76.9	338.6	19.3	77.3	62.3
16-64	2 398.3	1 753.7	644.6	202.0	2 600.3	453.5	3 053.8	7.8	85.2	78.5
20-64	2 343.1	1 702.6	640.4	179.2	2 522.3	289.0	2 811.3	7.1	89.7	83.3
Women										
15-24 years	256.4	219.8	36.5	64.9	321.3	278.8	600.1	20.2	53.5	42.7
25-34	454.9	303.2	151.7	37.2	492.1	89.8	582.0	7.6	84.6	78.2
35-44	536.7	338.1	198.6	25.4	562.1	58.4	620.5	4.5	90.6	86.5
45-54	523.8	359.0	164.8	25.2	549.0	72.4	621.4	4.6	88.4	84.3
55-64	402.9	271.8	131.1	18.6	421.5	159.5	581.0	4.4	72.6	69.4
65-74	51.4	40.3	11.1	..	53.3	459.7	513.0	..	10.4	10.0
15-74	**2 226.1**	**1 532.2**	**693.9**	**173.4**	**2 399.4**	**1 118.5**	**3 518.0**	**7.2**	**68.2**	**63.3**
of which										
15-19	62.9	56.5	6.4	26.8	89.7	187.6	277.2	29.9	32.3	22.7
20-24	193.5	163.4	30.1	38.1	231.6	91.2	322.9	16.5	71.7	59.9
16-64	2 172.8	1 490.0	682.8	170.1	2 343.0	613.2	2 956.2	7.3	79.3	73.5
20-64	2 111.8	1 435.4	676.4	144.6	2 256.4	471.3	2 727.7	6.4	82.7	77.4

Our work with a system for analysing LFS data is based on the structure in Chart 1. However, there are users in the central government that want other groupings by age. That is why we defined the first module for time series analysis for 240 time series in terms of thousands of persons each month: 16 age groups · 3 sex groups · 5 labour status categories = 240 series

In this way we have 240 series in thousands of persons and 240 series in monthly percentages. Each monthly series has a corresponding quarterly series defined as the average (in some cases, the sum) of three monthly values. To handle the data in Chart 1, we developed *Module 1* in the time series analysis system that uses 4 · 240 = 960 time series.

In this system of series, we have consistency in five ways in the data generated by the Swedish Labour Force Survey: consistency by age groups, sex groups, labour status categories, thousands of persons and corresponding per cent and also between monthly and quarterly values. These consistencies hold for original data before seasonal adjustment and our aim was to have the same consistencies after seasonal adjustment.

2.1 The moving measurement period

The measurement periods are chosen so that they consist of four or five full weeks. What is called "January" in the LFS may actually start somewhere in the interval 29 December – 4 January. When "January" starts in December, the New Year vacation period leads to hours worked at 22.5 million hours lower than the trend value (2004 in Chart 3) but equal to the trend value when "January" starts 1 January (2007 in Chart 3). This kind of moving measurement period makes seasonal adjustment very difficult.

Chart 2. Measurement periods in the LFS do not correspond to calendar months

	2002	2003	2004	2005	2006	2007	2008	2009	2010
"January"	31-Dec	30-Dec	29-Dec	03-Jan	02-Jan	01-Jan	31-Dec	29-Dec	04-Jan
	27-Jan	01-Feb	25-Jan	30-Jan	29-Jan	28-Jan	27-Jan	01-Feb	31-Jan
"February"	28-Jan	27-Jan	26-Jan	31-Jan	30-Jan	29-Jan	28-Jan	02-Feb	01-Feb
	24-Feb	23-Feb	22-Feb	27-Feb	26-Feb	25-Feb	24-Feb	01-Mar	28-Feb
"March"	25-Feb	24-Feb	23-Feb	28-Feb	27-Feb	26-Feb	25-Feb	02-Mar	01-Mar
	31-Mar	30-Mar	28-Mar	03-Apr	02-Apr	01-Apr	30-Mar	05-Apr	04-Apr
"April"	01-Apr	31-Mar	29-Mar	04-Apr	03-Apr	02-Apr	31-Mar	06-Apr	05-Apr
	28-Apr	27-Apr	25-Apr	01-May	30-Apr	29-Apr	27-Apr	03-May	02-May
"May"	29-Apr	28-Apr	26-Apr	02-May	01-May	30-Apr	28-Apr	04-May	03-May
	26-May	25-May	23-May	29-May	28-May	27-May	25-May	31-May	30-May
"June"	27-May	26-May	24-May	30-May	29-May	28-May	26-May	01-Jun	31-May
	30-Jun	29-Jun	27-Jun	03-Jul	02-Jul	01-Jul	29-Jun	05-Jul	04-Jul
"July"	01-Jul	30-Jun	28-Jun	04-Jul	03-Jul	02-Jul	30-Jun	06-Jul	05-Jul
	28-Jul	27-Jul	25-Jul	31-Jul	30-Jul	29-Jul	27-Jul	02-Aug	01-Aug
"August"	29-Jul	28-Jul	26-Jul	01-Aug	31-Jul	30-Jul	28-Jul	03-Aug	02-Aug
	25-Aug	24-Aug	22-Aug	28-Aug	27-Aug	26-Aug	24-Aug	30-Aug	29-Aug
"September"	26-Aug	25-Aug	23-Aug	29-Aug	28-Aug	27-Aug	25-Aug	31-Aug	30-Aug
	29-Sep	28-Sep	26-Sep	02-Oct	01-Oct	30-Sep	28-Sep	04-Oct	03-Oct
"October"	30-Sep	29-Sep	27-Sep	03-Oct	02-Oct	01-Oct	29-Sep	05-Oct	04-Oct
	27-Oct	26-Oct	31-Oct	30-Oct	29-Oct	28-Oct	26-Oct	01-Nov	31-Oct
"November"	28-Oct	27-Oct	01-Nov	31-Oct	30-okt	29-Oct	27-Oct	02-Nov	01-Nov
	24-Nov	23-Nov	28-Nov	27-Nov	26-Nov	25-Nov	23-Nov	29-Nov	28-Nov
"December"	25-Nov	24-Nov	29-Nov	28-Nov	27-Nov	26-Nov	24-Nov	30-Nov	29-Nov
	29-Dec	28-Dec	02-Jan	01-Jan	31-Dec	30-Dec	28-Dec	03-Jan	02-Jan
Easter	**29 /3 -1/4**	**18-21 Apr**	**9-12 Apr**	**25-28 Mar**	**14-17 Apr**	**6-9 Apr**	**21-24 Mar**	**10-13 Apr**	**2-5 Apr**

Chart 3. Disturbances of hours worked (millions/week) due to changing measurement periods

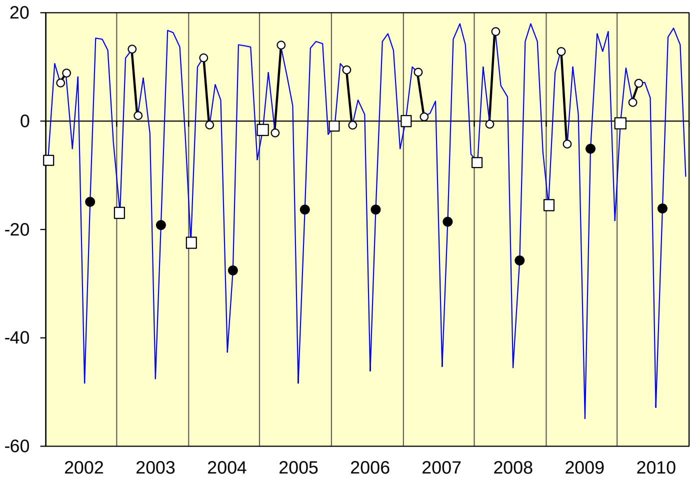
	2002	2003	2004	2005	2006	2007	2008	2009	2010
"January"	-7.2	-16.9	-22.5	-1.6	-0.9	0.0	-7.6	-15.5	-0.4
"March"	7.1	13.3	11.7	-2.1	9.5	9.1	-0.5	12.9	3.5
"April"	8.9	1.1	-0.7	14.1	-0.7	0.8	16.6	-4.2	7.0

In Chart 4 the same disturbances as in Chart 3 are shown. We use here the traditional additive time series model:

$y_t = TC_t + S_t + E_t$ or *original series = trend-cycle + seasonal component + residual*

After the estimation of the trend-cycle *TC*, the differences $y_t - TC_t$ in Chart 4 give a description of $S_t + E_t$. The values for "January" are marked as white squares, "March" and "April" when Easter may occur are marked as white circles and "August" as black circles.

Chart 4. Disturbances of hours worked, millions/week



There is no stable seasonal pattern for "January", as the values for $S_t + E_t$ depend on if the New Year is included in the LFS "January" or not.

"August" has moved one week between 2008–2009 with drastic effects on the seasonal pattern.

In addition, the estimation of the effects of calendar variation becomes difficult since LFS "March" and "April" are not always the calendar months that are used in time series analysis software for calendar corrections. In 2010, Easter Friday fell on 2 April but is included in LFS "March". Due to this the Easter effect during 2010 cannot be handled with e.g. X12-ARIMA or Tramo-Seats.

In Chart 2 above we can compare the LSF periods "July" and "August" for 2008 and 2009. These measurement periods move about one week between these years. As these two months have the strongest seasonal effects in many Swedish time series, th week that was moved destroyed the seasonal patterns in many LFS series. As this was the first time that "July" and "August" in the LFS had these time periods, the calendar effect could not be estimated with historical data. These disturbances then had to be handled as outliers.

As illustrated above, the moving measurement periods have consequences for the time series quality. If we measure the noise or the disturbances in the series with all hours worked by the standard deviation of the estimated time series residuals E_t, we get the following measure that can be compared with the sampling error:

– Standard error of the estimated time series residuals E_t: 3.9 million
– Standard error of the estimate according to sampling theory: 0.8 million

The moving measurement period is a quality issue that is much more important than the sampling error for all estimates concerning hours worked, hours absent from work, number of persons at work and persons absent from work. These are very important variables in the LFS and the errors generated by the moving measurement periods are thus a predominant part of the total survey error.

Good correction methods must be developed to overcome these disturbances. Otherwise, the usability of the Labour Force Survey will be limited.

2.2 Time series noise

Seasonally adjusted values y_t^* consist of trend plus noise or $y_t^* = TC_t + E_t$.

In charts 5a and 5b, the character of the times series describing unemployment rates in the USA and Sweden are compared. Seasonality is more pronounced in the Swedish series and noise is also more dominant in the Swedish series.

When charts 5a and 6a are compared, we find that they look similar – the seasonally adjusted US series is almost as smooth as the Swedish trend-cycle. Moreover, the unadjusted US series moves around the thick curve in a similar way as the Swedish seasonally adjusted series moves around the Swedish trend. It should be remembered that both the US and the Swedish series are unemployment for both sexes and all ages. This means that the Swedish series is the most aggregated unemployment series in the Swedish LFS – all other unemployment series are based on smaller samples and consequently have more random variation or more noise than this series.

The standard deviation of the noise in the Swedish series is $s(E_t) = 0.2$ and this is almost equal to the sampling theory based standard error of unemployment. So this noise reflects the true character of the Swedish series.

Chart 5. Unemployment rates in USA and Sweden, original and seasonally adjusted values

Chart 5a. USA, y_t (thin line) and y_t^* (thick line)

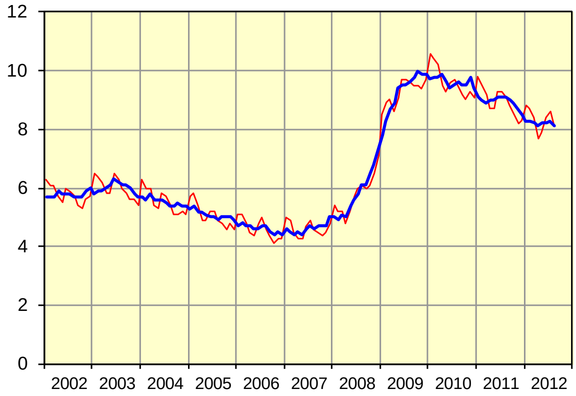


Chart 5b. Sweden, y_t (thin line) and y_t^* (thick line)

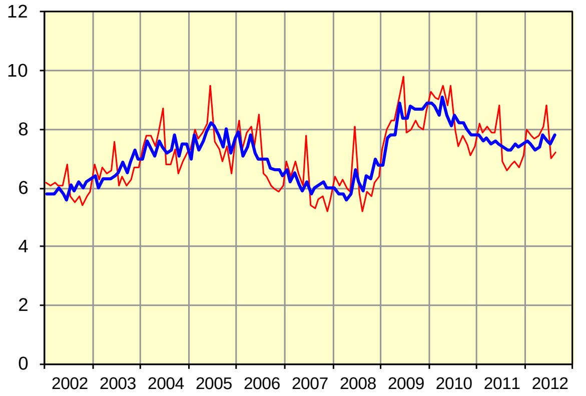


Chart 6. Unemployment rates in Sweden, seasonally adjusted values and estimated trends, *TC*

Chart 6a. Sweden, y_t^* (thin line) and *TC* (thick line)

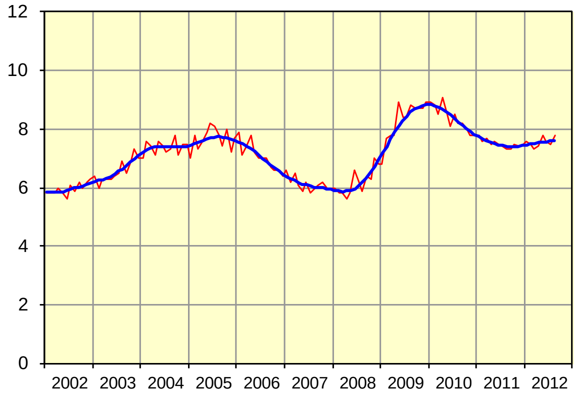


Chart 6b. Sweden, y_t^* (point of needle) and *TC*

We quote here the Quality Guidelines of Statistics Canada (2009):

> **12.1.2 Trend-cycle estimation**
> Seasonal adjustment of highly volatile series may not be enough to draw conclusion on the current trend-cycle direction. In those cases, further smoothing of the seasonally adjusted series is advisable to eliminate most of the irregular component. The resulting trend-cycle estimate is to be considered auxiliary information to the seasonally adjusted series.

The conclusions that we draw from the comparisons between Swedish time series and corresponding series from the USA in charts 5 and 6 are of a general character. Monthly Swedish series have as a rule stronger seasonal variation and more noise (irregular component or residuals) than series from the USA. So according to Statistics Canada's guidelines, further smoothing is practically always advisable with Swedish monthly series.

When the character of time series from small countries is different from time series from large countries such as the USA, the guidelines for time-series analysis should be different. According to our experience of Swedish time series, further smoothing, i.e. trend-cycle estimation is not only advisable but as a rule necessary – to measure rate of change we must use the estimated trend-cycle. And we do not consider the trend-cycle estimate as auxiliary information to the seasonally adjusted series; instead, we regard the seasonally adjusted series as auxiliary information to the estimated trend-cycle. First we judge the trend-cycle pattern TC_t and then we look at the last y_t* values. If the last seasonally adjusted values are above the estimated trend-cycle, this can be an indication of a turning point, e.g. that the trend-cycle could soon turn upwards.

As seasonally adjusted values y_t* consist of trend-cycle plus noise ($y_t* = TC_t + E_t$), then the difference between the seasonally adjusted series and the estimated trend-cycle is the series of estimated residuals E_t. As a rule, there is no interesting information in these residuals. The LFS is a sample survey and these time-series residuals in many cases only give a picture of the sampling errors. In the example above with the Swedish unemployment rate, the standard deviation of the noise was $s(E_t) = 0.2$ and this was almost equal to the sampling theory-based standard error of the total unemployment rate. Our interpretation is that this noise reflects the sampling error for each month.

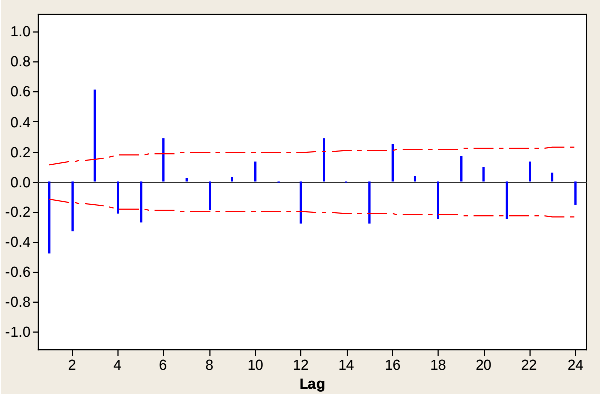
2.3 The effects of the panel design

The Swedish Labour Force Survey uses a panel design where each panel is interviewed once every third month. Each person is interviewed a total of eight times. When we compare surveys for e.g. January and April or the first and second quarters of a specific year, seven-eighths of the two samples consist of identical persons.

The idea behind this panel design is that quarterly rates of change should have small standard errors. However, the autocorrelation functions of all time series will be a mixture of the true autocorrelations on the labour market and artificial autocorrelations created by the sample design.

These disturbing autocorrelations due to panel effects make the ARIMA-models complicated and much more difficult to identify and estimate. As we have a system with about 1 250 series, we must use automatic model selections in Tramo-Seats or X12-Arima. Since the ARIMA-models are complicated, the chosen models will not be stable over time; when more data are added, different ARIMA-models may be chosen.

Chart 7. Autocorrelation function for $\nabla\nabla^{12}$ of Employed 55–64 years both sexes



The autocorrelations for lags 3, 6, ... have been generated by the panel design. The correlation at lag 3 is very strong for this category.

This autocorrelation function is complicated and does not follow a standard pattern.

The panel design will also disturb the estimated time series components *TC*, *S* and *E*. This is illustrated in charts 8 and 9, where we have simulated monthly and quarterly series. In all these simulations, we have a population where 70% are employed each month and quarter. So the true *TC* in all examples is constant and equal to 70. The needles in charts 8a, 9a, 8c and 9c are the true sampling errors. We have no seasonality and no other disturbances, so these sampling errors are the true times series residuals *E*.

The charts 8a–8d show series generated with new independent simple random samples (SRS) each month – no panel design at all. The quarterly series are generated, as in the LFS, as the mean of three months. The sample size is 1 000, which is a normal sample size for many domains in the LFS.

The charts 9a–9d show series generated according to the panel design used in the LFS. One out of eight panels is new every month. Each person in the population has the same employment status for all months. The quarterly series are generated as the mean of three months. The sample size is 1 000 and the autocorrelation at lag 3 is 0.74 in the monthly series.

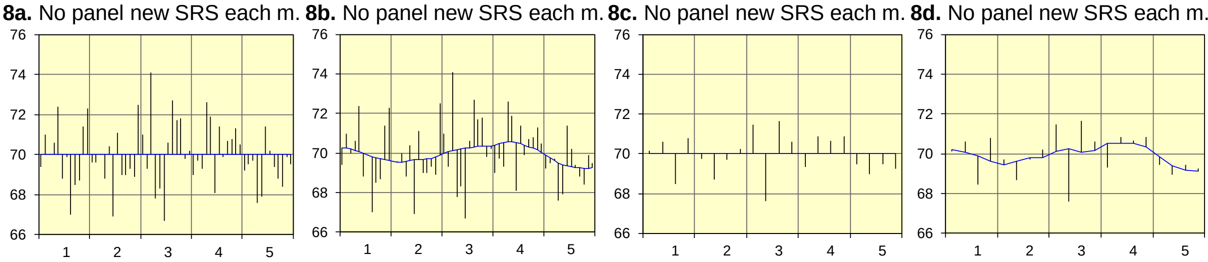
Chart 8 and Chart 9. Effects of the panel design in the LFS.

Monthly series
True *TC* and *E*
8a. No panel new SRS each m.

Monthly series
Estimated *TC* and *E*
8b. No panel new SRS each m.

Quarterly series
True *TC* and *E*
8c. No panel new SRS each m.

Quarterly series
Estimated *TC* and *E*
8d. No panel new SRS each m.

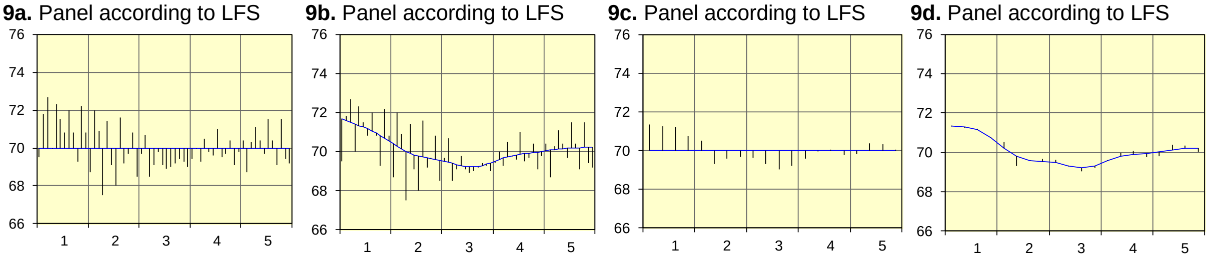


Monthly series
True *TC* and *E*
9a. Panel according to LFS

Monthly series
Estimated *TC* and *E*
9b. Panel according to LFS

Quarterly series
True *TC* and *E*
9c. Panel according to LFS

Quarterly series
Estimated *TC* and *E*
9d. Panel according to LFS



The trend-cycles in charts 8 and 9 have been estimated by applying moving averages similar to the filters in X12-ARIMA.

The problems with the panel design are clearly shown in charts 9c and 9d. Due to the panel design, the quarterly sampling errors are almost the same as during the previous quarter and these sampling errors are misinterpreted as a trend-cycle. The monthly series in charts 9a and 9b also have the same problem – nearly the same sampling errors come back after three months and this will distort the trend-cycle.

The estimated irregular component *E* also becomes distorted; in Chart 9d it looks as if there are almost no random disturbances. As most of the true *E* component is included in the estimated *TC* component, the estimated *E* component consists of values close to zero.

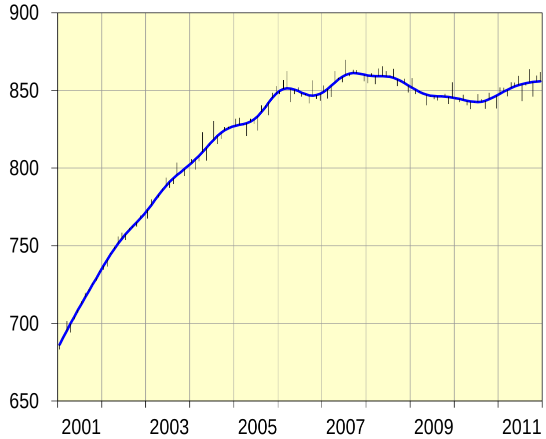
The charts 8a–8d show that even when the residuals are uncorrelated, the trend-cycle is estimated with errors due to the well-known Slutzky-Yule effect; a moving average of a random series oscillates. However, the errors are smaller than in cases where the residuals are positively autocorrelated.

In the charts below, the seasonally adjusted values y^* are the points of the needles; the curve is the estimated trend-cycle *TC*; and the vertical lines, the needles, are the estimated time series residuals, *E*.

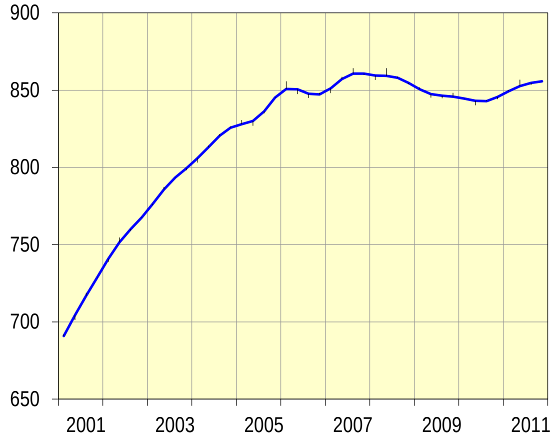
The main drawback of the panel design used in the Swedish LFS is that the estimated times series residuals especially in the quarterly series become too small and give a false impression of high time series quality. This is illustrated in Chart 10 below where the standard error of the estimated *E*-component (2.2) is much smaller than the standard error of the estimate according to sampling theory (4.8).

Chart 10. Thousands of persons employed, 55–64 years both sexes, *y, estimated *TC* and *E***

10a. Monthly series
Standard error of estimated *E*: 5.1 thousands
Sampling standard error of estimate: 8.5 thousands



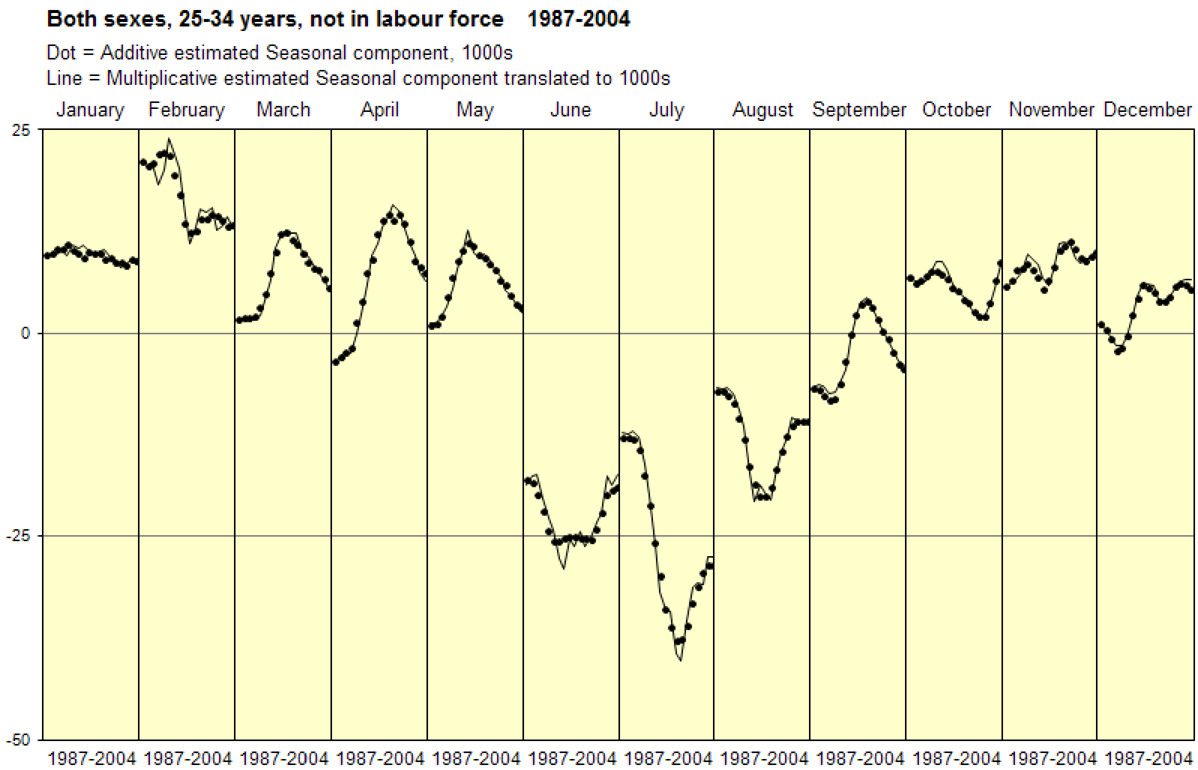
10b. Quarterly series
Standard error of estimated *E*: 2.2 thousands
Sampling standard error of estimate: 4.8 thousands



2.4 The seasonal patterns

Additive or multiplicative model? The 240 series, which are the series describing thousands of persons by sex, age group, and labour status categories, were tested with the *transform function = auto* option in X12-ARIMA. For all series, except 11, the AICC-criterion indicated that additive time-series models were better than multiplicative. The series with the biggest difference AICC(additive model) – AICC(multiplicative model) was seasonally adjusted with both models. However, the estimated seasonal components are almost the same; this is illustrated in Chart 11 below. As the seasonal component in X12-ARIMA is adaptive, additive and multiplicative time series models can generate similar estimates. The estimated S_t component for the multiplicative model can be transformed into normal scale of 1000s persons by $S_t = y_t - y_t^*$

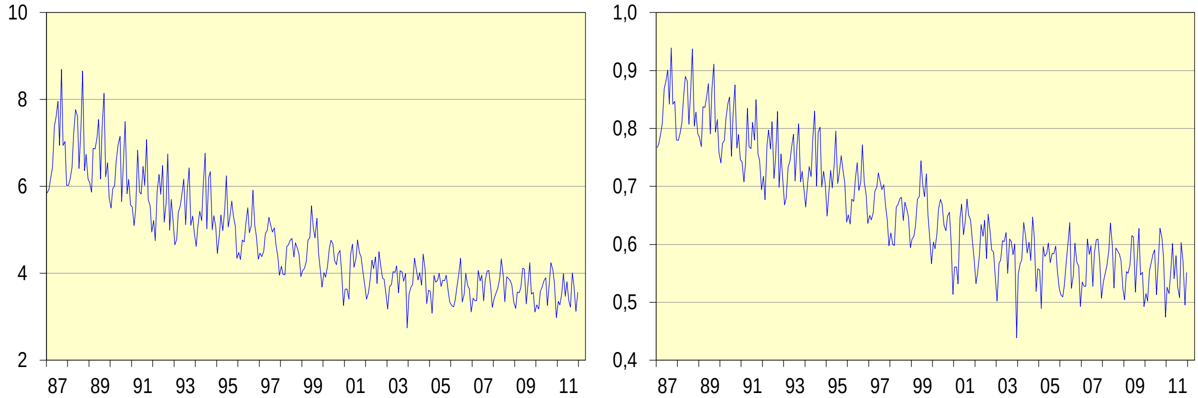
Chart 11. Additive and multiplicative seasonal components are almost the same



We also analysed the series describing hours actually worked. Only one series of these was clearly multiplicative – hours worked within agriculture, forestry and fishing. In Chart 12a, we can see that variation is more than 2 million in the beginning of the series but only about 1 million at the end. After logarithmic transformation, the variation is about the same independent of the series level. The conclusion is that the series has multiplicative seasonal patterns. However, additive and multiplicative seasonal adjustments are equally good; the standard deviation of E_t from additive adjustment is 0.22, and the corresponding standard deviation from the multiplicative adjustment is 0.23 when the multiplicative component is transformed into normal scale by $E_t = y_t^* - TC_t$.

Chart 12. Hours worked within agriculture forestry and fishing, normal and logarithmic scales

12a. Hours per week, millions   12b. Log^{10}(Hours per week, millions)



3 How to achieve consistency

The structure of LFS data must be taken into account when systems are developed for seasonal adjustment. The additivity necessary for *consistency* between different series is determined by the multi-dimensional frequency tables that are generated by the Labour Force Survey. The *moving measurement period* will disturb series describing persons at work or absent, hours worked or absent, but not the series describing stable states as employed or unemployed. The time series *noise* makes trend-cycle estimates important and the *panel design* will generate artificial autocorrelations at lag 3 in monthly series. When these autocorrelations are strong, the sampling errors will be misinterpreted as trend-cycle, and it may be risky to use ARIMA-models for estimation of seasonality and trend as in Tramo-Seats. The fact that *additive* time series models can be used for LFS data will simplify the work of deriving consistent seasonally adjusted values.

3.1 Different methods to achieve consistency

The monthly and quarterly time series generated by the LFS are consistent before seasonal adjustments are made. This means that series for sums of categories agree with the sums of their parts. But after outlier corrections and seasonal adjustment, the adjusted values are as a rule no longer consistent.

Many statisticians prefer the *direct method* for seasonal adjustment, where each series is adjusted as best as possible without regards to other series. The sum and the parts are inconsistent, but that is considered a natural consequence of the fact that statistical estimation never can be perfect.

The users often want consistency between a seasonally adjusted sum and the sum of the seasonally adjusted parts. As a rule, they use the *indirect method* where the parts are seasonally adjusted and the sum of the seasonally adjusted parts is used as the seasonally adjusted sum. Due to the fact that the sum now has not necessarily been adjusted in the best possible way, many statisticians do not want to use the indirect method. E.g. in *ESS Guidelines on Seasonal Adjustment* (Eurostat 2009), the direct method is recommended except when the parts have significantly different seasonal patterns.

Both the direct and the indirect methods have the disadvantage that all information is not used. In the direct method the information regarding the additivity conditions is not used; in the indirect method the information in the aggregated series is not used despite the fact that the aggregated series as a rule have better time series quality, as the time series noise is less disturbing due to relatively smaller sampling errors.

According to the ESS Guidelines (op. cit.), it is acceptable to use the direct method and adjust the seasonally adjusted values to achieve consistency, if there are strong user requirements for consistency. A method for this has been developed by Stuckey, Zhang and McLaren (2004). Their method has been tested and implemented for use in the Swedish quarterly National Accounts. This work is reported in Elezovic, Odencrants and Xie (2009).

3.2 Preconditions

A reference group with experienced analysts from the central government was formed for the work in developing a system for consistent seasonal adjustment. If each time series is counted as four – e.g. persons employed monthly, employment rates monthly, persons employed quarterly and employment rates quarterly, the reference group wanted about 5 000–6 000 series to be seasonally adjusted. The total number of published series that can be seasonally adjusted is about 30 000 including both monthly and quarterly series. This shows the importance of the LFS in Sweden – it is used by many analysts, and different users need different series so that the total number of important series is large.

We defined the following preconditions for our work with the system for time series analysis:

1. About 4 000 series should be included in the system. These series describe labour status category by sex and age group, subdivisions of labour status category by sex and age group, and hours worked by sex, degree of attachment to the labour force and kind of economic activity. The structure of LFS data will be regarded when designing the system.
2. Seasonally adjusted values and estimated trend-cycle values should be *consistent* in three dimensions: sex, age group, and labour status category; i.e. employed, unemployed, not in labour force. Seasonally adjusted series for number of persons and corresponding per cent of population should be consistent. Seasonally adjusted monthly series and corresponding quarterly series should also be consistent. Pre-treatment as adjustments for trading day, moving holiday and moving measurement period should be consistent. Outlier corrections should also be consistent. Different seasonally adjusted series for hours worked should be consistent in a similar way.
3. Adjustments to attain consistency should be as small as possible. Real data should not be subject to unnecessary corrections and adjustments.
4. Subject matter competence should be used when deciding if a value is an outlier or an indication of a real rapid change.
5. The system will be handled by a small number of persons working under pressure. These persons are not specialised time series analysts; they belong to the ordinary subject matter staff who are responsible for the LFS. Risks for mistakes should be eliminated as much as possible. Robust methods should therefore be chosen.

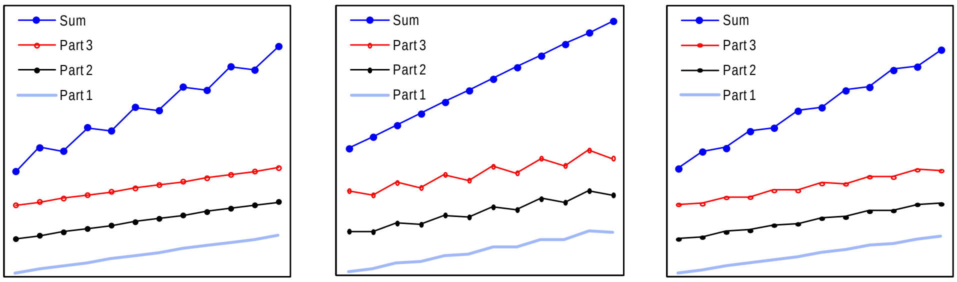
3.3 Choice of method

As we mentioned in Section 3.2, both the indirect and direct methods do not use all available information. If this information is used in the estimation of time series components, it should be possible to improve the quality of these estimates. It is this methodological challenge together with strong user demands for consistency in a system with about 4 000 time series that have induced us to work with developing a system for consistent seasonal adjustment.

How to fulfil precondition 2 above regarding consistency? Consistent seasonal adjustment in a three-way frequency table can be achieved in different ways.

In Chart 13, we compare three methods, the common indirect method, the method developed by Stuckey et al., and the method we have developed. Our method will be explained in detail in the following sections.

Chart 13. Three methods for consistent seasonal adjustment



Indirect method

The parts are seasonally adjusted, the sum is indirectly derived as the sum of the seasonally adjusted parts.

In a three-dimensional table we have six marginal distributions; then many series will be indirectly adjusted in this way.

This is a serious drawback for LFS data that is organised in multi-dimensional tables.

Stuckey, Zhang, McLaren

All series are seasonally adjusted by direct method, and then the parts are consistency adjusted to be consistent with the sum.

Difficult to use for three-dimensional tables.

If it is used, only one series in each table will be seasonally adjusted with the direct method, all other series belonging to the six other marginals and the disjunct cells will be consistency adjusted step by step.

Wallgren, general

All series are seasonally adjusted by direct method, then all series are adjusted to be consistent. If more series are consistency adjusted, the adjustment for each series can be smaller.

Adjustments for consistency depend on the volatility of each series – high volatility gives proportionally more adjustments than low.

Easy to use for multi-dimensional tables.

3.3.1 Our method adapted for the LFS

First, we eliminate inconsistencies as much as possible. Thereafter, we use the general method to adjust for remaining inconsistencies. Inconsistencies can have a number of causes:

a) If multiplicative models are used for some series, the sum and the parts will be inconsistent. Based on the comparisons between additive and multiplicative models for LFS data in Section 2.4, we decided to use additive time series models for all series in the system for consistent seasonal adjustment of LFS data.

b) Outlier corrections are as a rule done independently for each series, which creates inconsistencies. Our method for consistent outlier corrections is described in Section 3.4.

c) Calendar corrections are also done independently for each series, which also creates inconsistencies. Our method for consistent corrections for calendar variation and the effects of moving measurement periods are described in Section 3.5.

d) ARIMA-models. In Seats, the estimated trend-cycles and seasonally adjusted values are derived from the ARIMA-models. Due to the structure of ARIMA-models, the models for the parts and the model for the sum of the parts will be inconsistent and consequently so will the trends and seasonally adjusted values. The panel design in the LFS will also make the ARIMA-models complicated. These facts, together with precondition 5 in Section 3.2 concerning the need to use simple and robust methods, led us to decide to use X12-ARIMA in the system for consistent seasonal adjustments of LFS data.

e) ARIMA extrapolations. In X12-ARIMA, seasonally adjusted values and estimated trend-cycles for the last part of the series are based on ARIMA extrapolations. As these extrapolations are done with ARIMA-models, the extrapolations will be inconsistent – a sum and its parts will as a rule not agree. The ARIMA extrapolations are made consistent with the method based on a linear model for the frequency table generating the system of time series.

f) Trend and seasonal filters. In X12-ARIMA different moving average filters can be used for estimates of seasonally adjusted values and for the trend-cycle estimates. We decided to use the same trend and seasonal filters for all series whereby no inconsistencies are created. We prefer the 23-point Henderson trend filter and the s3x5 seasonal filter due to the strong volatility in Swedish series.

3.3.2 Combining estimates

In the tables published by the LFS, there are several examples where there are many estimates of the same parameter. E.g. the seasonally adjusted total number of unemployed is estimated directly, but can also be obtained as the sum of seasonally unemployed men and unemployed women. These three estimated seasonally adjusted values are as a rule inconsistent.

How can several estimates that perhaps are inconsistent be combined into one estimate with better quality? This is a standard example in a course in statistical theory:

Assume that we have two independent estimators y_1 and y_2 of the parameter θ with variances σ_1^2 and σ_2^2. How can we combine these estimators in an optimal way?

The answer is the estimator $\hat{\theta} = \sigma_2^2 /(\sigma_1^2 + \sigma_2^2) \cdot y_1 + \sigma_1^2/(\sigma_1^2 + \sigma_2^2) \cdot y_2$.

The variance of $\hat{\theta}$ is smaller than both σ_1^2 and σ_2^2. So instead of *two* inconsistent estimates of the same parameter, we arrive at *one* estimate with better quality. We get the same estimator of the parameter that we now denote with β, by using a regression model:

$y_i = \beta \cdot x_i + \varepsilon_i$ where $x_i = 1$ and the weights $1/\sigma_i^2$ are used for $i = 1, 2$.

3.3.3 Combining estimates in a one-way frequency table

Assume that we have the one-way frequency table below with inconsistent values regarding one specific month in column (1). These values can either be seasonally adjusted values, estimated trend-cycle values or ARIMA extrapolated values to be used in X12-ARIMA for estimation at the endpoint of the series. As the number of employed both sexes should be employed men + employed women, all three cells in column (1) could be derived if the two parameters β_1 and β_2 were known.

Sex	Employed, 1000s inconsistent values y_i (1)	Variance for the residuals in the ARIMA-model (2)	Regression model (3)	Employed, 1000s consistency adjusted $\hat{y}_i$ (4)
Men	2 300	320	$\beta_1 \cdot 1 + \beta_2 \cdot 0$	2 322
Women	2 100	310	$\beta_1 \cdot 0 + \beta_2 \cdot 1$	2 121
Both sexes	4 500	830	$\beta_1 \cdot 1 + \beta_2 \cdot 1$	4 443

How can the three observed values y_i be used to estimate the two parameters β_1 and β_2? In the same way as we used regressions analysis in the example in Section 3.3.2, we can derive the consistent values $\hat{y}$ in column (4). The model in column (3) has two dummy variables for men and women respectively:

$y_i = \beta_1 \cdot x_1 + \beta_2 \cdot x_2 + \varepsilon_i$

We also use weights here and these weights are inversely proportional to the variance of the three series ARIMA-residuals in column (2). Volatile series will receive low weights and non-volatile series will get heavy weights.

3.3.4 Combining estimates in multidimensional tables

Assume that we have the following two-dimensional frequency table with inconsistent ARIMA extrapolated values for a specific month. In this table we have neither consistency, so that:

Both sexes = *Men + Women* nor consistency so that:

Labour force = *Employed + Unemployed* nor consistency so that:

Population = *Labour force + Not in labour force*

Inconsistent table, 1000s of persons

	Employed	Unemployed	Not in labour force	Labour force	Population
Men	2 300	60	450	2 400	2 700
Women	2 100	50	500	2 200	2 600
Both sexes	4 500	100	900	4 700	5 200

We can also use the method here that uses weighed regressions analysis, where the weights are inversely proportional to the variance of the ARIMA-residuals for each series.

Variances, ARIMA-residuals

	Employed	Unemployed	Not in labour force	Labour force	Population
Men	320	100	250	248	0.43
Women	310	85	275	279	0.46
Both sexes	830	230	685	691	1.25

The regression model will have six x-variables, one dummy variable for each of the six disjunct cells (shaded) in the table below. The fifteen y-variables are in the 5x3 way table above with inconsistent values.

Regression model

	Employed	Unemployed	Not in labour force	Labour force	Population
Men	β_1	β_2	β_3	$\beta_1 + \beta_2$	$\beta_1 + \beta_2 + \beta_3$
Women	β_4	β_5	β_6	$\beta_4 + \beta_5$	$\beta_4 + \beta_5 + \beta_6$
Both sexes	$\beta_1 + \beta_4$	$\beta_2 + \beta_5$	$\beta_3 + \beta_6$	$\beta_1+\beta_2+\beta_4+\beta_5$	$\beta_1+\beta_2+\beta_3+\beta_4+\beta_5+\beta_6$

With weighed regression analysis we obtain the following frequency table that is consistent in two dimensions:

Consistent table, 1000s of persons

	Employed	Unemployed	Not in labour force	Labour force	Population
Men	2 299.0	50.6	350.4	2 349.6	2 700.0
Women	2 119.7	47.7	432.6	2 167.4	2 600.0
Both sexes	4 418.7	98.3	783.0	4 517.0	5 300.0

The regression analysis used to obtain the table with consistent estimates is described in the table below. The design matrix is the matrix with the six dummy variables that describes the structure of the time series defined by the two-dimensional frequency table.

Regression analysis

	Design matrix								
y	x_1	x_2	x_3	x_4	x_5	x_6	s^2	$weight = 1 / s^2$	$\hat{y}$
2 300	1	0	0	0	0	0	320.00	0.00313	2299.0
60	0	1	0	0	0	0	100.00	0.01000	50.6
450	0	0	1	0	0	0	250.00	0.00400	350.4
2 400	1	1	0	0	0	0	248.00	0.00403	2349.6
2 700	1	1	1	0	0	0	0.43	100.00000	2700.0
2 100	0	0	0	1	0	0	310.00	0.00323	2119.7
50	0	0	0	0	1	0	85.00	0.01176	47.7
500	0	0	0	0	0	1	275.00	0.00364	432.6
2 200	0	0	0	1	1	0	279.00	0.00358	2167.4
2 600	0	0	0	1	1	1	0.46	100.00000	2600.0
4 500	1	0	0	1	0	0	830.00	0.00120	4418.7
100	0	1	0	0	1	0	230.00	0.00435	98.3
900	0	0	1	0	0	1	685.00	0.00146	783.0
4 700	1	1	0	1	1	0	691.00	0.00145	4517.0
5300	1	1	1	1	1	1	1.25	100.00000	5300.0

The three population values have intentionally obtained heavy weights of 100. In this way, the population values that are defined by the population register and used as the frame for the LFS are kept constant.

With this kind of linear model, we have adjusted the outlier corrections, the calendar and moving “months” corrections and the ARIMA-extrapolations used by X12-ARIMA. In this way, all input series to the seasonal adjustment in X12-ARIMA become consistent. Since the same filters are used for all series the output from X12-ARIMA is also consistent.

3.3.5 Our method for seasonal adjustment of LFS data

A *k*-way frequency table is additive in *k* dimensions. These additivity conditions can be expressed with a linear model as explained in Section 3.3.4. We will use linear models of this kind to adjust estimates that are not additive, but should be additive. We thereby improve the quality of the estimates by using auxiliary information on the additivity of the underlying parameters.

Let us use *Module 1,* the first times series analysis module we designed, to illustrate our general method. This module uses data from a three dimensional frequency table with persons by age, sex and labour status category. Sixteen age groups, three sex groups and five labour status categories are used. In all, $16 \cdot 3 \cdot 5 = 240$ series are the input into the module according to the categories below:

15-19	15-24	16-19	16-24	18-24	20-24	25-34	35-44	45-54	55-59	60-64	55-64	16-64	18-64	65-74	15-74

Men	Women	Both sexes

Employed	Unemployed	Not in labour force	In labour force	Population

Out of these series only $10 \cdot 2 \cdot 3 = 60$ series are from disjunct cells, the others are combinations of these:

15	16-17	18-19	20-24	25-34	35-44	45-54	55-59	60-64	65-74

Men	Women

Employed	Unemployed	Not in labour force

If these 240 time series are analysed with X12-ARIMA, we may obtain 240 estimated seasonal components for a specific month, or we may obtain 240 estimated outlier effects for a specific month, or we may obtain 240 ARIMA extrapolations for a month in the future. These seasonal components, outlier effects or extrapolations can be inconsistent – the additivity conditions that the original time series values follow will as a rule not hold when each series is analysed independently from the other series.

Each month, we obtain 240 estimates defined by 60 parameters in this way. How should these 240 estimates be used to obtain the best estimates of the 60 parameters? The idea is to combine the information in all 240 series. The indirect method for seasonal adjustment would use only the information in the 60 disjunct series and the remaining 240 – 60 = 180 series would have been derived indirectly as sums of different combinations of the 60 disjunct series. So the indirect method will discard the information in the majority of the series in the system. The discarded information should also have better quality than the 60 series used, as the 180 series that are discarded are on a more aggregate level and have smaller coefficients of variation.

We define the vector $\mathbf{y}$ as the vector with the 240 values for a specific month that may be inconsistent. The vector $\boldsymbol{\beta}$ is the vector of 60 unknown parameters for the disjunct cells, and the design matrix $\mathbf{X}$ is the matrix of dummy variables that defines how each of the 240 values are derived from the 60 disjunct values. The vector $\hat{\mathbf{y}}$ is the vector of 240 consistent values and these values are obtained from the regression analysis. As weights in the regression analyses, we use $1/s^2$ where s^2 is the variance of the ARIMA residuals for each series.

It should be noted that with the method we use for LFS data, we only adjust outlier corrections, calendar and moving "month" corrections, and the extrapolated ARIMA values. When we have eliminated these inconsistencies, we can use the seasonally adjusted values and estimated trend-cycle values from X12-ARIMA exactly as they are without adjustments.

The method is also flexible and easy to use. After *Module 1,* the first time series analysis module we designed, had been used for publishing seasonally adjusted LFS data, we developed *Module 2* where subdivisions of the labour status categories from Module 1 are analysed. All 960 series with persons by detailed labour status categories, age class and sex are seasonally adjusted in Module 2. For the subdivision of employed persons we use the outlier corrections and ARIMA-extrapolations from Module 1. And the values from Module 1 are not altered – they are given very heavy weights in the regression analysis so that they remain unchanged in the same way that the population values in Section 3.3.4 were kept fixed. This makes it easy to obtain consistency between the 240 series in Module 1 and the 960 series in Module 2.

In this way we have obtained consistent seasonally adjusted values and trends for 240 + (960 - 240) = 960 series regarding *persons* by labour status category, age and sex.

After that, we obtain 960 consistent series by division with population values regarding *per cent of population* (or labour force for unemployment rate).

By taking the averages of the three months belonging to the same quarter, we also obtain 960 consistent *quarterly series* regarding *persons* by labour status category, age and sex. And finally, by division with population values, we obtain 960 consistent quarterly series regarding *per cent* of the population or the labour force.

The methods used to go from 960 series on number of persons monthly, to $4 \cdot 960$ series regarding number of persons, per cent and both monthly and quarterly series, consist of simple computations, which make the risk of errors small.

3.4 Consistent ARIMA-outlier corrections

After comparing output for independent X12-ARIMA runs for many LSF series, we found that the outlier corrections generate many inconsistencies. In this section we describe our method for consistent outlier correction in a system of time series defined by a multidimensional frequency table.

3.4.1 Outlier detection in time series from frequency tables

There are options for automatic outlier detection and correction in both X12-ARIMA and Tramo. For each time series, the software searches for extreme ARIMA-residuals and tests for different kinds of outliers by including appropriate regression variables in the model. We illustrate our method with the following system of 12 quarterly time series:

Chart 14. Persons by sex and labour status category, 1000s 2nd quarter 1992

	Men	Women	Both sexes
Employed	2 199.8	2 080.3	4 280.1
Unemployed	135.7	77.0	212.7
Not in labour force	429.7	523.0	952.7
Population	2 765.2	2 680.3	5 445.5

In this table there are six disjunct cells and two marginal distributions that define the system of times series and the additivity conditions. The system consists of nine LFS time series and three population series, where the population series are smooth and therefore are not seasonally adjusted.

We analysed the nine LFS series with the outlier option in X12-ARIMA. After automatic detection of additive outliers with critical value 2.5, the following significant additive outliers (AO) were found:

Chart 15. Significant outliers after automatic outlier detection in X12-ARIMA

	Employed			Unemployed			Not in the labour force		
	Men	Women	Both sexes	Men	Women	Both sexes	Men	Women	Both sexes
AO1989.3	0	0	0	-6.4	0	0	0	0	0
AO1992.2	0	0	27.0	0	0	0	0	0	0
AO1992.4	0	0	0	-8.9	0	0	0	0	0
AO1994.3	0	0	0	17.8	0	21.2	0	0	0
AO1996.1	0	0	28.1	0	0	0	0	0	0
AO1998.3	0	0	0	0	10.9	0	0	-16.9	0
AO2000.3	0	0	-31.2	0	0	0	0	19.2	32.5
AO2003.3	0	0	0	-8.6	0	0	0	13.9	0
AO2004.3	0	18.5	0	0	0	0	-16.1	0	0

Standard procedure is to correct for these outliers and proceed with seasonal adjustment of the nine series. However, the outlier effects in Chart 15 are inconsistent. E.g. during the second quarter 1992, the number of employed both sexes is 27 thousand too high according to the estimated value. But then either employed men and/or women must also be 27 thousand higher than expected and the categories unemployed and/or not in the labour force must be 27 thousand lower than expected.

The next step is therefore to estimate all effects for the quarters in question. With one exception (men not in the labour force 2004 Q3), the outlier effects from Chart 15 remain in Chart 16 but now we have estimates for all series.

Chart 16. Estimation of all outlier effects for the quarters with significant outliers

* =significant with critical value 2.5	Employed			Unemployed			Not in the labour force		
	Men	Women	Both sexes	Men	Women	Both sexes	Men	Women	Both sexes
AO1989.3	-4.4	3.4	-2.5	**-6.1***	-8.4*	-12.5*	8.5	5.2	10.1
AO1992.2	12.3*	13.5*	**25.9***	-0.4	-4.8	-5.5	-11.8*	-9.4	-21.5*
AO1992.4	8.3	2.0	11.1	**-8.5***	-1.5	-7.5	2.8	2.8	4.6
AO1994.3	1.7	-4.4	-1.8	**17.2***	5.8	**22.2***	-16.6*	-0.5	-18.7*
AO1996.1	15.9*	11.4*	**27.6***	-2.6	-0.2	-4.3	-11.7*	-9.2*	-23.4*
AO1998.3	4.5	5.7	11.9	2.0	**12.1***	12.5*	-7.0	**-19.2***	-22.8*
AO2000.3	-16.0*	-12.4*	**-28.2***	2.1	-2.7	0.4	13.0*	**18.9***	**30.4***
AO2003.3	4.6	-4.3	-1.2	**-8.7***	-0.1	-8.9	3.9	**11.8***	15.5
AO2004.3	2.2	**14.8***	15.3	-2.0	-0.5	-3.4	**-0.2**	-5.9	-7.6

The estimated outlier effects in Chart 16 above are not consistent. E.g. for 1989 Q3, the effects for employed men + employed women are not equal to both sexes ($-4.4 + 3.4 \neq -2.5$) and the three effects for men do not sum to zero ($-4.4 -6.1 + 8.5 \neq 0$). As the population of men should not be adjusted, this sum should be zero.

Using the methods described in the previous sections, the inconsistent estimates in Chart 16 can be improved if the information in the additivity conditions is used as auxiliary information. After this improvement, we obtain the new estimated outlier effects in Chart 17 that are consistent.

Chart 17. Consistent estimates of all outlier effects for the quarters with significant outliers

	Employed			Unemployed			Not in the labour force		
	Men	Women	Both sexes	Men	Women	Both sexes	Men	Women	Both sexes
AO1989.3	-3.5	3.1	-0.4	-5.4	-7.7	-13.1	8.9	4.6	13.5
AO1992.2	12.3	13.9	26.2	-0.5	-4.7	-5.2	-11.9	-9.1	-21.0
AO1992.4	7.2	0.3	7.5	-8.3	-1.5	-9.8	1.1	1.1	2.2
AO1994.3	1.0	-4.5	-3.4	16.8	5.4	22.2	-17.9	-0.9	-18.8
AO1996.1	15.6	11.0	26.6	-3.0	-0.9	-3.9	-12.6	-10.0	-22.7
AO1998.3	4.7	6.5	11.2	1.6	11.7	13.4	-6.4	-18.2	-24.6
AO2000.3	-15.5	-14.1	-29.6	2.5	-3.1	-0.6	13.0	17.2	30.2
AO2003.3	4.6	-7.7	-3.1	-8.5	-1.5	-10.0	4.0	9.2	13.1
AO2004.3	2.2	11.2	13.4	-1.9	-2.3	-4.1	-0.3	-8.9	-9.2

The regression analysis is described in Chart 18. In the first column with numbers in Chart 18, the inconsistent estimated outlier effects from X12-ARIMA are given. The second column contains the standard deviations of the estimated outlier effects. These standard deviations are used for the weights in the regressions analysis. In the last column, we have the fitted values from the regression analysis that are the final consistent estimates of the outlier effects.

Note that we have added three rows with zeros as outlier effects for the series with the three populations that have very small standard errors (arbitrarily set to 0.1 by us). In this way we use the auxiliary information that

employed + unemployed + persons not in the labour force = the population

By setting the standard deviation extremely small (0.1), we keep the population effect unchanged. This way of intentionally keeping some variables constant in our method for consistent seasonal adjustment of LFS data can be used to add auxiliary information for improving the estimates.

Chart 18. Consistency adjustments of outlier effects, 1000s, 2nd quarter 1992

		y	s	x_{11}	x_{12}	x_{21}	x_{22}	x_{31}	x_{32}	Weights	Fits
Employed	Men	12.3	4.2	1	0	0	0	0	0	0.06	12.3
Employed	Women	13.5	4.2	0	1	0	0	0	0	0.06	13.9
Employed	Both sexes	25.9	7.1	1	1	0	0	0	0	0.02	26.2
Unemployed	Men	-0.4	2.3	0	0	1	0	0	0	0.19	-0.5
Unemployed	Women	-4.8	3.1	0	0	0	1	0	0	0.10	-4.7
Unemployed	Both sexes	-5.5	3.5	0	0	1	1	0	0	0.08	-5.2
Not in labour force	Men	-11.8	4.2	0	0	0	0	1	0	0.06	-11.9
Not in labour force	Women	-9.4	3.8	0	0	0	0	0	1	0.07	-9.1
Not in labour force	Both sexes	-21.5	6.8	0	0	0	0	1	1	0.02	-21.0
Population	Men	0	0.1	1	0	1	0	1	0	100.00	0.0
Population	Women	0	0.1	0	1	0	1	0	1	100.00	0.0
Population	Both sexes	0	0.1	1	1	1	1	1	1	100.00	0.0

Many times series published by National Statistical Institutes come from frequency tables which are additive in one, two, three or more dimensions. The nine time series in Chart 19 are additive in two dimensions. If we denote these series by $y_{11} – y_{33}$, the additive model with disturbing effects (D) can be written:

$y_{11} = TC_{11} + D_{11} + S_{11} + E_{11}$, where the disturbing effect D can be the outlier effect and/or the calendar effect that influences the observed value y_{11}.

From the additivity conditions and the fact that the population values are fixed, we get the following additivity conditions:

Rows: $D_{13} = D_{11} + D_{12}$ $D_{23} = D_{21} + D_{22}$ $D_{33} = D_{31} + D_{32}$

Columns: $D_{11} + D_{21} + D_{31} = 0$ $D_{12} + D_{22} + D_{32} = 0$

Chart 19. Persons by sex and labour status category, 1000s, 2nd quarter 1992

	Men	Women	Both sexes
Employed	y_{11} = 2 199.8	y_{12} = 2 080.3	y_{13} = 4 280.1
Unemployed	y_{21} = 135.7	y_{22} = 77.0	y_{23} = 212.7
Not in labour force	y_{31} = 429.7	y_{32} = 523.0	y_{33} = 952.7
Population	2 765.2	2 680.3	5 445.5

The observed values y, the true trend-cycle components TC, the true seasonal components S, and the true residuals E follow the same additivity conditions. The estimated D effects in Chart 16 do *not* follow these conditions, but the estimated D effects in Chart 17 do follow these conditions.

According to Chart 15, $D_{13} = 27.0$, but that cannot be the only $D \neq 0$, there must be more. In Chart 17, the final estimate of $D_{13} = 26.2$ and there are also other nonzero estimated D components for this quarter.

Our conclusion is: The whole system of time series must be considered when the components D, TC, S and E are estimated.

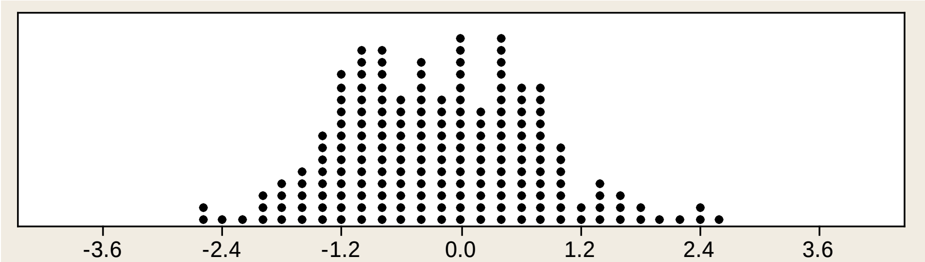
3.4.2 Outlier corrections in Module 1

In this section we show some output from Module 1 with data up to June 2009 and July 2009. After updating the data files, the first output shows the result from a test of the consistency of all variables that have been updated with values for June 2009. The regression residuals where the consistency is tested have the following minimum and maximum. As all residuals are almost zero, this shows that input was consistent.

Variable:	N	Minimum	Maximum	
Regression residuals	240	-0.000602	0.000749	measured in 1000s of persons

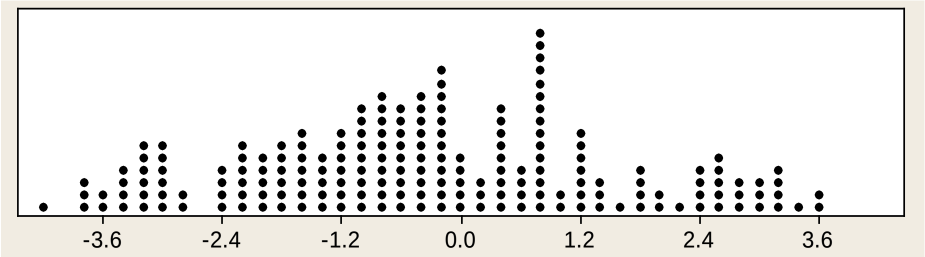
The first use of X12-ARIMA is an analysis where the standardised ARIMA-residuals of all input series are plotted. The plot with standardised residuals for June 2009 shows that all 240 input series look normal – there are no signs of outliers during this month. As a rule, these residual plots are similar to this plot.

June 2009:



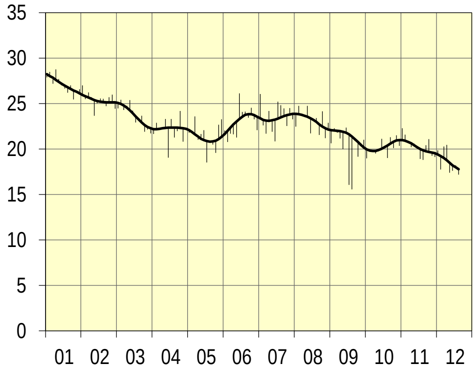
The same kind of plot for July 2009 shows that many input series have standardised ARIMA-residuals that are extreme. It was decided that July 2009 was a month that required outlier corrections. The outlier effects for all series during July 2009 were estimated as in charts 16–17 in Section 3.4.

July 2009:

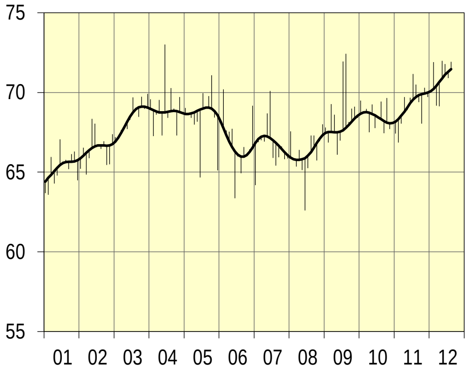


The outlier effects were large for young persons employed and not in the labour force. The charts below describe both sexes 15–19 years, 2001–2012.

Employment rate, %



Not in labour force rate, %



Traditionally we think of one series at a time when we search for outliers. Each month we ask: *Is the last value in this series an outlier or not?* If the answer is *yes*, we correct the last value.

But when we have LFS data from frequency tables, we cannot think of one outlier in one cell in the table only – there must be a number of cells in the table for a specific month that are parts of the same outlier effect. That is why we show ARIMA residuals for all series in the system in the residual plots above. So the question with LFS data should be: *Are there outlier effects in the system of series this month or not?* If the answer is *yes*, we correct all values in the system for the last month. So there is only one decision every month for the system of 240 series, not 240 independent decisions.

This means that automatic outlier corrections should not be used; instead, those responsible for the LFS make one decision every month for the whole system. This decision should be based on the plot of ARIMA residuals above and knowledge of the labour market and the data collection process. If the residual plot shows extreme residuals:

– Are there labour market interventions or a strike this month? These effects should be modelled with Tramo or REGARIMA in X12. This interesting outlier effect should be reported to the public.
– How did the data collection process work this month? This should be modelled as an uninteresting outlier.
– Are we expecting a turning point on the labour market? This should not be modelled as an outlier.

3.4.3 Seasonal outliers in X11

In X12-ARIMA there are two kinds of outlier corrections that can be used. First, there is the ARIMA-residual based outlier option that we have used in the previous sections. This option is exactly the same that is used in Tramo, and that is the only outlier option in the Tramo-Seats software.

There is another option in X12-ARIMA that was introduced in the early versions of X11. This option is based on the irregular component E_t that is estimated in the X11 command of X12-ARIMA. In Section 3.4, we analyse a system of 12 time series, nine LFS series and three population series. Out of 72 quarterly values for these nine series, 34 quarters have no seasonal outliers and 38 quarters have seasonal outliers according to this outlier option in the X11 command. The outlier effects for these 38 quarters are inconsistent in the same way as in Chart 15 in Section 3.4.1. As a consequence, the seasonally adjusted values will also be inconsistent.

We have a system of 240 series in Module 1, and the outlier option in the X11 command will give us inconsistent outlier effects for most months. Our conclusion is that if you want consistent seasonal adjustment of LFS data, this outlier option in the X11 command cannot be used. Because this would lead to that almost all the data used would become artificial outlier corrected data instead of real LFS data.

3.5 Calendar variation and moving "months"

In Section 2.1, we mention the problems that arise because the measurement periods in the LFS are moving. LFS "January" can start anywhere between 29 December and 4 January. Consequently, New Year vacations are sometimes included and sometimes not included in the measurement period that is called "January" in the LFS. The seasonal pattern will differ depending on this. Swedish LFS data have very strong seasonality due to the long summer vacations that usually take place during July. If the measurement period that is called "July" moves and starts somewhere between 28 June and 6 July, this strong seasonal pattern will be disturbed. In Chart 2 in Section 2.1, the moving "months" in the LFS are shown.

Another consequence of these moving months is that the options for calendar corrections in standard software for seasonal adjustment are not suitable for LFS data. The number of Mondays, etc., that are used for calendar corrections are the number of Mondays in the calendar months, not the LFS measurement periods. The variables describing Easter are also not suitable for LFS data for the same reason.

Summing up: We have strong calendar variation and strong variation due to moving measurement periods in the LFS. Standard software for seasonal adjustment and calendar corrections are not adopted for LFS data. This means that methods suitable for the kind of time series that the LFS generates have been lacking.

3.5.1 Hours actually worked – the effects of moving months

Chart 20a shows the problem with moving months and Chart 20b shows our solution, where calendar variation and the effects of moving months have been reduced. The standard error of the monthly estimate is 0.8 million hours according to the sampling theory estimate. The standard deviation of the irregular time series component E_t is 3.9 million in the uncorrected series. After corrections for moving months and calendar variation, the standard deviation of the irregular component has been reduced to 0.8 million, the same magnitude as the sampling error.

Chart 20. Hours worked all employed, millions per week, seasonally adjusted values and trends

Chart 20a. Original series without correction s(E) = 3.9

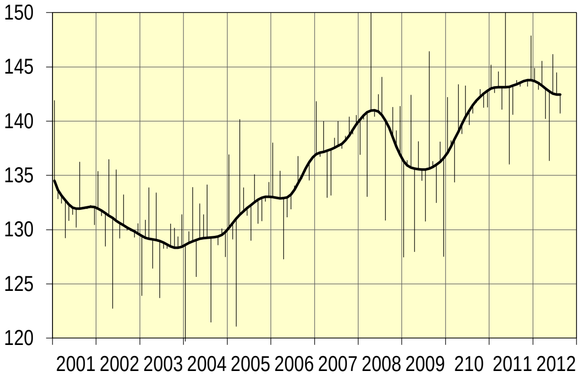
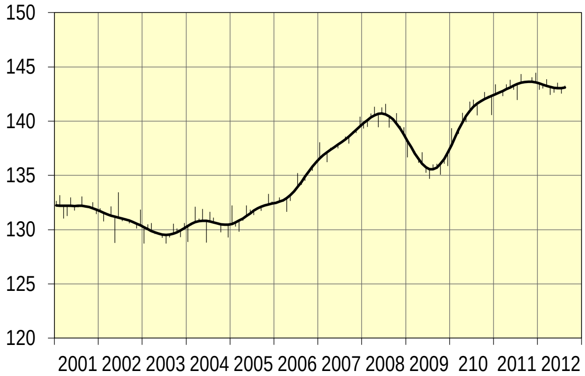


Chart 20b. Corrected for moving months and calendar variation. s(E) = 0.8



In the table below the standard deviation of E_t for the uncorrected series in Chart 20a is described for different months. The most problematic months are January, April, March, May and December where there are holiday effects. New Year moves between "December" and "January", Easter moves between "March" and "April" and other holidays between "April" and "May". During "August", "June" and "July" the effects of summer vacations are disturbed by moving measurement periods.

Jan	Apr	Aug	Mar	May	Dec	Jun	Jul	Oct	Nov	Sep	Feb
6.4	6.1	5.3	5.2	4.8	3.8	3.5	2.9	1.8	1.1	1.0	0.9

3.5.2 Our correction method

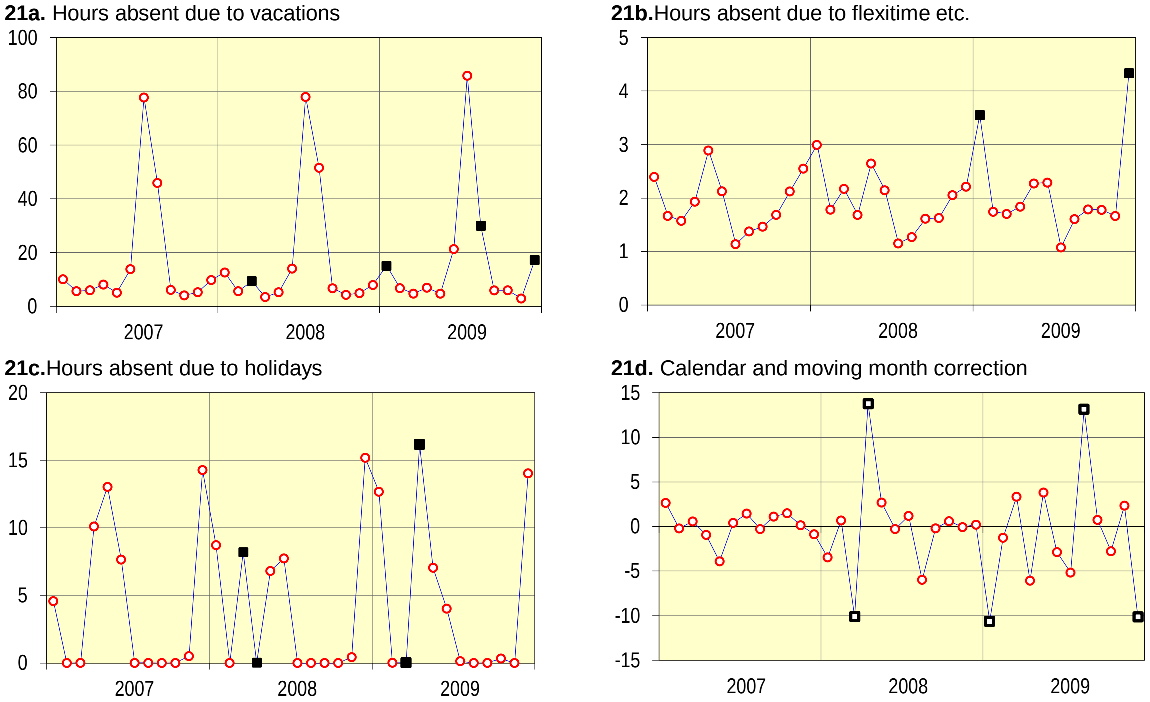
The moving month effect can be handled with an extra question in the LFS interview. In the Swedish LFS, this extra question is included and the hours worked are split between months for measurement weeks that belong to two months. The Swedish National Accounts obtain this data on hours worked by industry and calendar months. These data are, however, not consistent with other LFS variables; this is discussed in Statistics Sweden (2012).

We have developed another method that uses information on reasons for being absent from work. The effects of Christmas, New Year, Easter and the other Easter related holidays during the spring are measured in the LFS interview. In addition, the effects of moving measurement periods have consequences for being absent from work for some reasons.

In Chart 21a, it can be seen that vacations during August 2009 (one of the four black boxes) were low due to a moving month effect. The LFS “August” was moved from a start at 28 July during 2008 to 3 August during 2009 and as a consequence hours absent went down. In Chart 21d the correction necessary has been estimated to be approximately 14 million hours.

In Chart 21a and 21b, we can see the effects of moving December and January. LFS “January” 2009 started 29 December 2008 and LFS “December” 2009 ended 3 January 2010. Both hours absent due to vacations and due to flexitime increased as the effect of absence for New Year celebrations. The corrections for this are seen in Chart 21d (white squares for January and December 2009).

Chart 21. Hours absent from work, millions, all employed



In Chart 21c the black squares show the effect of Easter in March 2008, which can be compared with the usual pattern with Easter during April as in 2009. The corrections of hours worked are illustrated in Chart 21d.

The correction is subtracted from hours worked so that hours worked during March 2008 are increased by 8 million hours due to the Easter holiday absence and 2 million hours due to Easter vacations in Chart 21a.

How are the corrections in Chart 21d estimated? The first step was to analyse all series with hours absent to see where there are calendar effects and/or moving month effects. Five series were chosen due to these effects: vacations, flexitime, compensation for overtime, variations in working time and holidays.

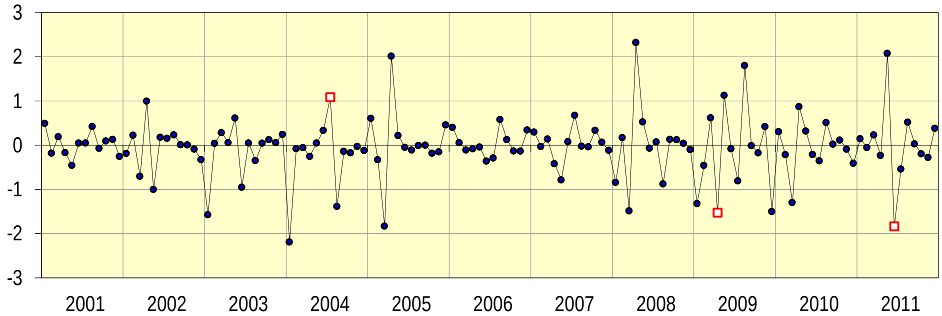
As hours worked are reported by sex, degree of attachment to the labour market and industry, monthly series with hours absent due to the five reasons above were generated for all combinations of sex, attachment and industry. All these monthly series were analysed with X12-ARIMA and consistent estimates of the irregular component E_t were derived. Each series with hours worked was corrected with the corresponding irregular component.

In Chart 22, the correction factors for two industries are shown. The first (red) square in Chart 22a shows that hours absent from work were 1 million hours *less* than normal during July 2004 in the financial industry. So hours actually worked was 1 million hours *more* than normal due to calendar variation and moving month effects, and should be corrected or *reduced* by 1 million hours.

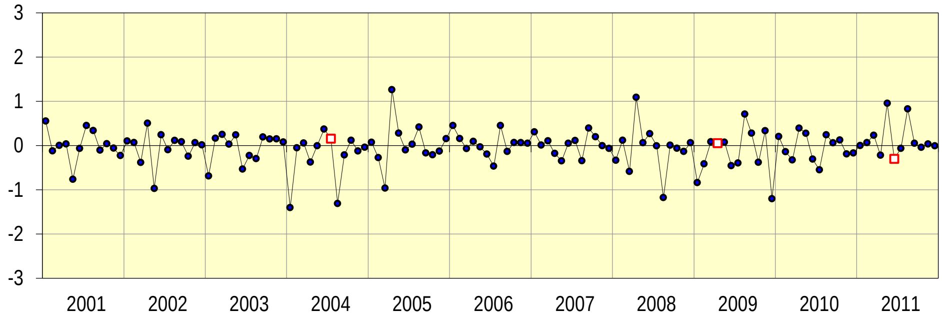
Two conclusions are clear from Chart 22. First, there are no trends, no business cycles and no seasonality in these correction factors. This means that the calendar and moving month corrections we use with this method do not change the *TC* and *S* components of hours worked.

Chart 22. Correction factors for calendar variation and moving months

22a. Financial intermediation, million hours absent from work less than normal absence



22b. Health and social work, million hours absent from work less than normal absence



The second conclusion is that the correction factors can be different for different industries. In Chart 22, we have marked three months with (red) squares in charts 22a and 22b. For these months, the corrections are quite different. For some industries the correction factors are very small.

Agriculture is an example – that the calendar and moving month effects are small for agriculture is very reasonable as cattle and fields are not influenced by such factors.

This method for corrections of calendar and moving month effects is different from the traditional methods based on regression models. The traditional methods use one or more x-variables that are proxy variables for calendar variation and estimate the effect of these x-variables on e.g. hours actually worked. It is difficult to model the effects of holidays such as Christmas. Depending on many factors, the effect can differ between years, e.g. the weather can increase or decrease the amount of vacations taken.

Our approach here is that we do not estimate effects; instead, we use the exact relation between hours absent from work and hours actually worked. And for each combination of sex, attachment to the labour market and industry, we have information on hours absent and hours worked for exactly the group of persons that belong to each specific domain of study.

In Wallgren and Wallgren (2012, page 15), we used the traditional approach to adjust for moving measurement periods. There we defined an x-variable that described the distance between midpoint of the actual measurement period and the midpoint of each month.

Chart 23. How much can different methods reduce disturbances?

	Correction with regression model in Wallgren (2012)	Correction with exact information of hours absent in this report
Time series residuals without correction for moving measurement period	**86** thousands of persons at work	**3.9** million hours worked
Time series residuals after correction for moving measurement period	**36** thousands of persons at work	**0.8** million hours worked
Standard error of estimate according to sampling theory	**18** thousands of persons at work	**0.8** million hours worked

Summing up:
Hours worked and number of persons at work are important series in the LFS. Without efficient methods to adjust for calendar variation and the effects of moving measurement periods, the time series quality of these series would be very bad.

The traditional regression based methods used in standard time series software are not suitable for LFS data. Both X12-ARIMA and Tramo-Seats use methods for *calendar* months. The LFS measurement periods are quite different.

The method we have developed has the following advantages:

– The corrections are consistent, e.g. hours worked for women + hours worked for men = hours worked for both sexes after corrections.
– The corrections are successful; this is illustrated in charts 20 and 23.
– It is easy to do the corrections that are suitable for any choice of domain of study – the information for all domains is in the LFS dataset.

4 Evaluation of the method

Let us compare the methods developed in Chapter 3 with the preconditions that are mentioned in Section 3.2. We have now about three years of experience from production of seasonally adjusted series with the new methods.

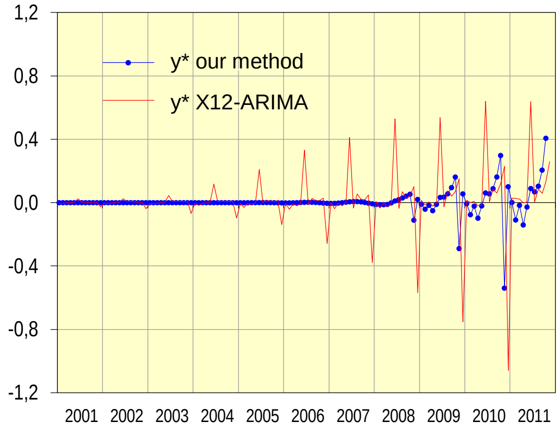
1. *"About 4 000 series should be included in the system."*
   In Modules 1 and 2, the 960 series of persons by sex, age and labour status category are the inputs into the system and this means that about 4 000 series are seasonally adjusted, including series on per cent of population and quarterly series. More than 100 series regarding hours worked are handled in Module 3. The methods developed thus can handle a large number of time series and produce the seasonally adjusted values that users demand.
2. *"Seasonally adjusted values and estimated trend-cycle values should be consistent. Pre-treatment as adjustments for outliers, trading day, moving holiday and moving measurement period should be consistent."*
   The methods developed meet these conditions.
3. *"Adjustments to attain consistency should be as small as possible. Real data should not be subject to unnecessary corrections and adjustments."*
   Only outlier effects, ARIMA extrapolations and corrections for calendar variation and moving months are adjusted. After that, the output from X12-ARIMA can be used without further adjustments – all 4 000 seasonally adjusted series and estimated trends are consistent.
4. *"Subject matter competence should be used when deciding if a value is an outlier or an indication of a real rapid change."*
   A system of more than 4 000 time series are seasonally adjusted without any automatic outlier correction methods. Every month, those responsible for the LFS judge the residual plot of all standardised residuals for each module. A decision is taken: Should the system of series in this module be outlier corrected or not? If "Yes", all series are corrected so that the corrections are consistent. If the answer is "No", the results are published without outlier corrections. This decision is also based on subject matter considerations. In this way, the LFS staff always knows and understands what corrections have been made. Overediting and overuse of outlier corrections are two related issues, where there are risks that normal random variation leads to the replacement of real data by artificial data. Three years of experience with the new way of handling outliers shows that it works. With a system of 4 000 series, you can expect about 40 series with significant "outliers" with the critical value 2.5. And with the LFS data, more series will be involved – if e.g. employed both sexes are too high, then employed men and women also must be too high, etc. This shows that the standard outlier approach is not suitable for LFS data.
5. *"The system will be handled by a small number of persons working under pressure. Risks for mistakes should be eliminated as much as possible."*
   The production system that has been developed has been used since January 2010 without any mistakes. More and more series are published. The IT-system is being improved to eliminate risks for mistakes.

4.1 Revisions when one new value is added

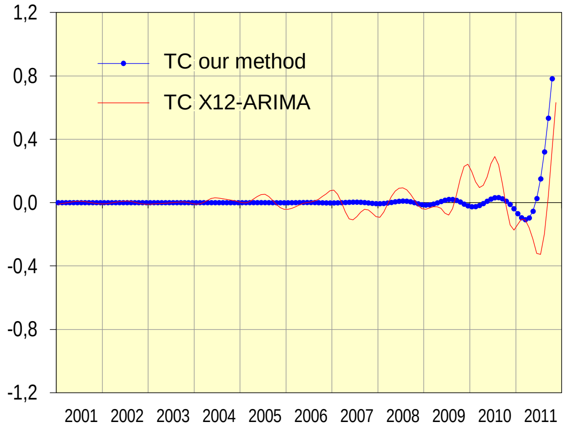
A well-known problem is that old estimates of the times series components are revised when new time series values are added. With the methods we have developed for LFS data, these revisions are limited to the last four years. With our method, the outlier effects are not revised when new data are added. Then the filter used for the estimates of the seasonal component is the main cause of revisions backwards. In Chart 24 the revisions with our method and default X12-ARIMA are compared. When a new observation is added, the seasonal outlier effects are revised in X12-ARIMA that cause revisions for many years backwards. The results in Chart 24 come from the series with hours worked, where we have added one observation for January 2012 and compared the new estimates based on data up to December 2011 with the previous estimates.

Chart 24. Revisions of old estimates when one new observation is added

24a. Revisions of seasonally adjusted values



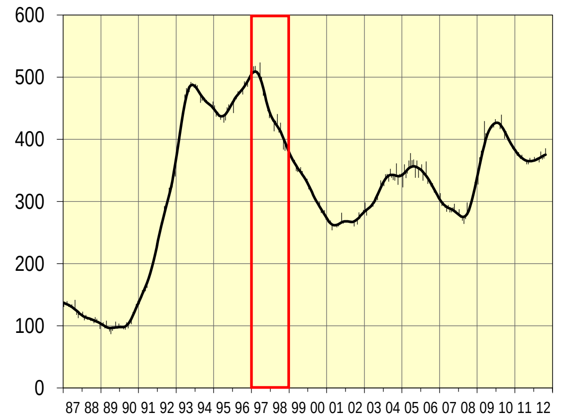
24b. Revisions of estimated trend-cycle values



4.2 Turning point revisions

One important aspect of time series analysis is how soon a turning point is detected. We have compared default X12-ARIMA with our method for the period January 1997–December 1998 when there was a sharp turning point. For each series in Module 1, we compared the 24 end point estimates for each series with the final estimates based on the whole series. In Chart 25 the maximum revisions among the 24 values for each series are compared. On the whole, our method shows smaller revisions than the estimates produced with default settings of X12-ARIMA.

Chart 25. Maximum absolute revisions of first estimate compared with final estimate, %



	Seasonally adjusted y*		Trend-cycle TC	
Unemployed, 1000s	Our method	X12	Our method	X12
Men 16–19	15.1	28.3	10.7	23.3
Men 20–24	8.0	9.3	11.0	15.9
Men 25–34	5.0	7.0	8.1	10.6
Men 35–44	3.6	7.3	5.8	7.2
Men 45–54	7.3	9.7	6.5	13.1
Men 55–59	7.4	6.1	8.0	12.7
Men 60–64	12.0	12.7	16.0	28.3
Women 16–19	37.1	30.6	20.0	37.0
Women 20–24	11.4	16.0	10.5	11.5
Women 25–34	7.8	14.5	16.1	20.7
Women 35–44	7.5	22.4	9.9	18.1
Women 45–54	8.6	6.8	8.0	9.7
Women 55–59	13.5	17.1	7.4	15.1
Women 60–64	17.3	40.1	20.1	39.5
Mean:	**11.5**	**16.3**	**11.3**	**18.8**

5 The method of presentation

Cross section statistics are quantitative – here we estimate *parameters*. In contrast, time series statistics are much more qualitative – here we estimate *patterns*. "Has unemployment started to go up?" is an example of a qualitative issue that is typical for time series statistics.

The conclusion is that when we publish time series statistics, charts are essential. There are important quality issues related to charts – are the charts misleading, or interesting and informative? When we work with seasonal adjustment, it is not sufficient to discuss the methods used to estimate the time series components. We must also discuss the methods used for graphical presentation. In the system we have developed, charts are important and we describe these charts in this section.

5.1 Needle charts

In Section 2.2, charts 6a and 6b are examples of two different ways of illustrating seasonally adjusted data and estimated trend-cycles. Chart 6a is the traditional way with zigzag lines for the seasonally adjusted values and a curve for the trend-curve. In Wallgren et al. (1996), we introduced the *needle chart* for this kind of time series data and Chart 6b is an example of this kind of chart (and also Chart 26 below). The following time series are illustrated with a needle chart:

– The trend-cycle is described with the smooth curve.

– Seasonally adjusted values are described by the endpoints of the needles.

– The times series residuals are described by the length of each needle.

Presenting seasonally adjusted values with zigzag lines emphasizes the time series noise or the irregular pattern, and the chart gives a restless impression. The curve in the needle chart emphasizes the long-term development, but what is special to each individual point in time is also described by the needles. This is why we recommend needle charts.

5.2 Measuring and illustrating change

Rate of change can be measured by comparing seasonally adjusted values, original values or estimated trend-cycle values. We compare these measures for the series describing hours worked from the Swedish LFS.

Chart 26. Hours worked, employed 15–74 years, million hours per week

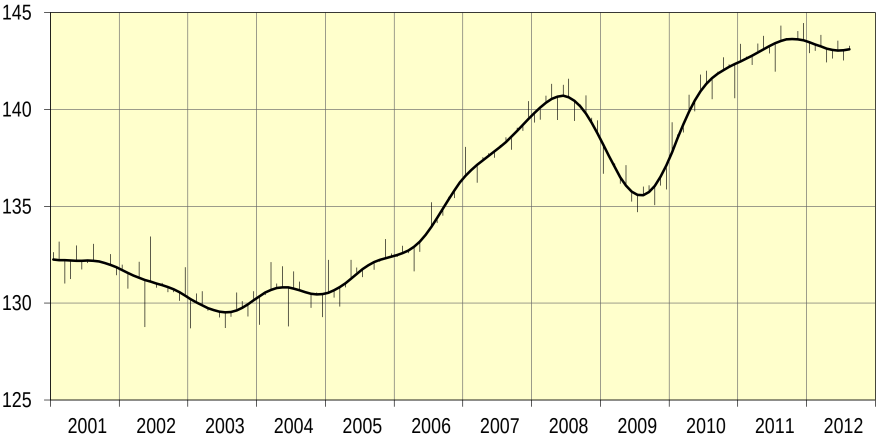
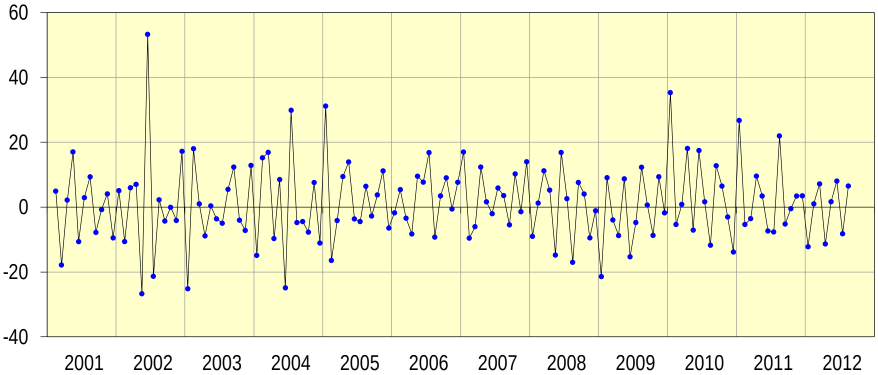


Chart 27. Rate of change measured by seasonally adjusted values y_t^*/y_{t-1}^*

Per cent per year



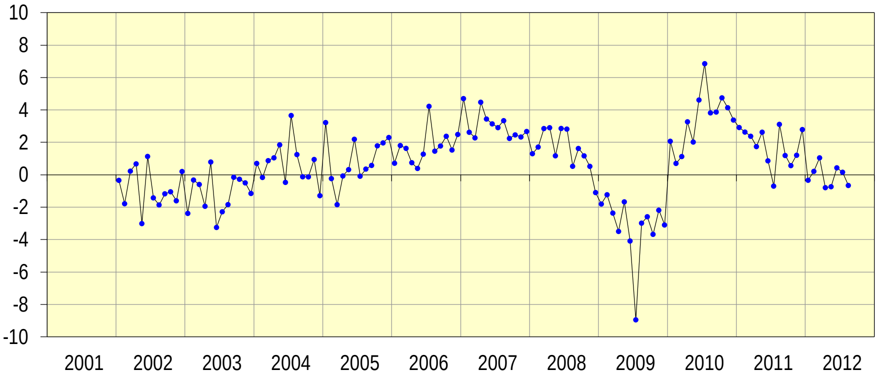
Why is seasonal adjustment important? Because then we can compare all points of time, e.g. the two last months. It is quite common to report change as per cent per month or per year comparing this month's seasonally adjusted value with the seasonally adjusted value for the previous month. In Chart 27 we measure change as per cent per year, but if we had taken per cent per month, the chart pattern would have been the same.

Is there any meaningful information in Chart 27? Can anyone use that information for decision making? If the chart says +10% this month and -9% next month, must you then change all decisions every second month? What is the quality of the information in Chart 27?

Almost all charts based on monthly seasonally adjusted values in Sweden look like Chart 27 above and that is why we warn everyone about measuring change in this way. In Section 2.2 we stated that Swedish monthly data are too volatile, instead of seasonally adjusted values we must use trend-cycle values. In Chart 29 below, the rate of change is measured by comparing the last two values of the estimated trend-cycle (red curve, curve without dots) and that measure is much more meaningful.

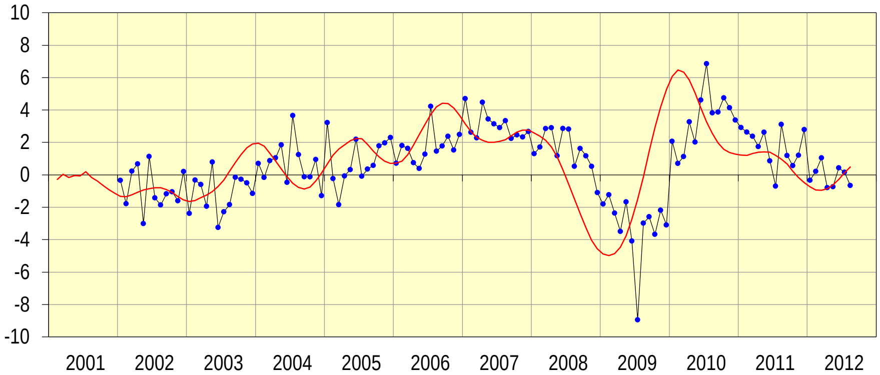
Chart 28. Rate of change measured by original values y_t/y_{t-12}

Per cent per year



Another common way of measuring change is to compare this month's original value with the value for the same month in the previous year. It is much easier to see a clear pattern in Chart 28 than in Chart 27. In Chart 28 we can see that there is an economic crisis during 2009, and it seems that the turning point in the rate of change is in the middle of 2009. But change measured in this way does not tell us what is happening now; it tells us what has happened during the last 12 months. We do not know if that change happened last month or 11 months ago. On the average, signals are delayed about six months by this way of measuring change. This delay can be seen in Chart 29 where this way of measuring change is compared with a measure where this month's trend-cycle value is compared with the trend-cycle value for the previous month.

Chart 29. Rate of change measured by original values y_t/y_{t-12} and trend TC_t/TC_{t-1}



We have decided not to use the measures of change in charts 27 and 28 in the system for time series analysis of Swedish LFS data. The only measure of change we use is based on the estimated trend-cycle values.

5.3 Monthly reports

Every month, a number of Excel files with tables and charts are updated. For all series presented in charts, tables with the following content are included in the same Excel file:

		Original value millions of hours worked	Corrected for calendar and moving month	Seasonally adjusted values	Estimated trend-cycle	Rate of change % per year
2012	1	141.6	139.7	142.9	143.47	-1.1
2012	2	153.0	153.2	143.0	143.36	-1.4
2012	3	154.9	153.4	143.9	143.25	-1.4
2012	4	142.6	144.5	142.4	143.14	-1.2
2012	5	145.0	148.1	142.6	143.07	-0.9
2012	6	148.0	148.4	143.5	143.03	-0.4
2012	7	93.2	92.0	142.5	143.05	0.2
2012	8	125.1	125.0	143.3	143.11	0.7

There are two different ways of presenting LFS data in charts. In Chart 30 all labour status categories for the same subpopulation are presented. Both data on persons and per cent of population are presented together. All in all, six charts are combined in the presentation for one subpopulation.

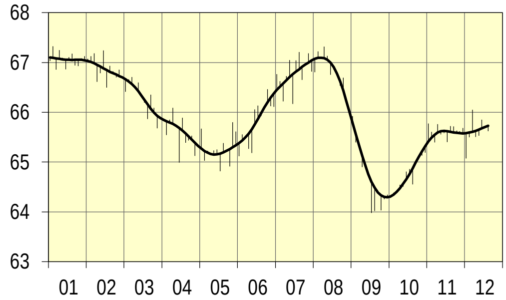
In Chart 31 we illustrate the relation between sex and age with one specific LFS category, e.g. unemployment. Chart 31 is an example of a *Trellis Chart* according to William Cleveland's terminology – a chart that consists of a table with charts in the tables cells. With this kind of chart, we can see the effects of sex and age on the category or variable that is described – in this case unemployment. It is important to have a common reference curve in all the charts that constitute Chart 31.

The presentations in charts 30 and 31 are quite different and the best idea is to include both in a presentation of LFS data.

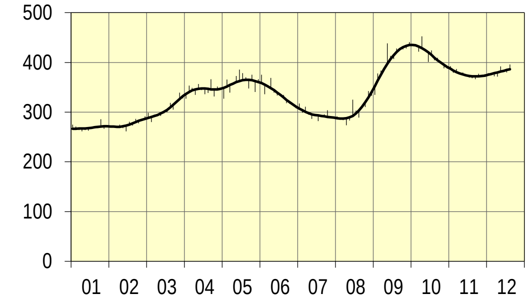
Chart 30. Population 15–74 years. Number of persons by labour status category

30a. Employed persons, 1000s

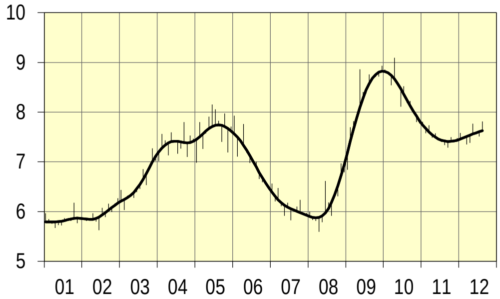
30b. Employment ratio, per cent



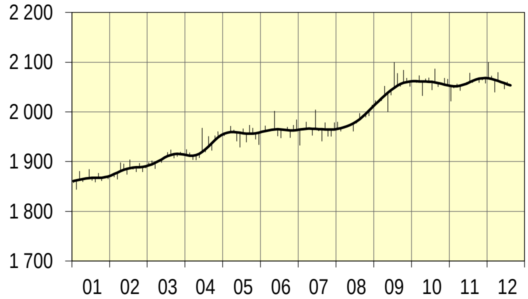
30c. Unemployed persons, 1000s



30d. Unemployment ratio, per cent



30e. Persons not in the labour force, 1000s



30f. Persons not in the labour force, % of population

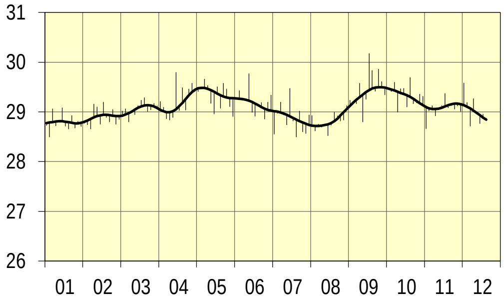
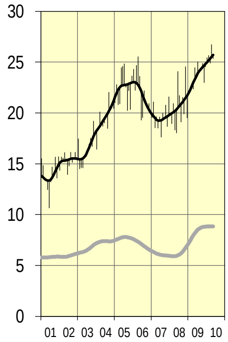
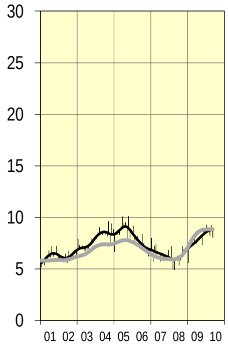


Chart 31. Unemployment rates by sex and age – grey reference curve: Both sexes 15–74 years

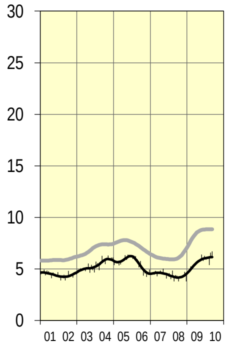
31a. Women 15–24



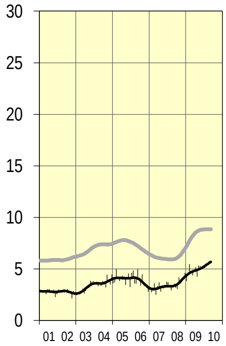
31b. Women 25–34



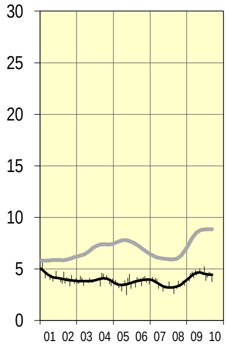
31c. Women 35–44



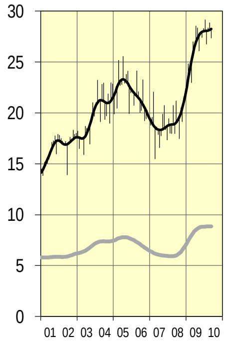
31d. Women 45–54



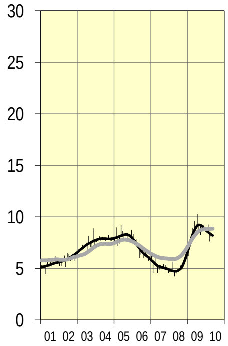
31e. Women 55–64



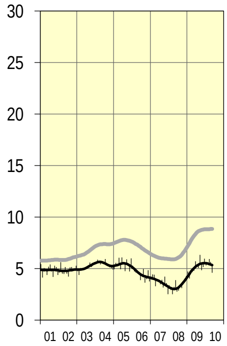
31f. Men 15–24



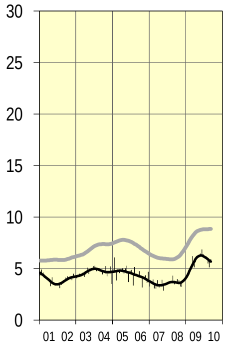
31g. Men 25–34



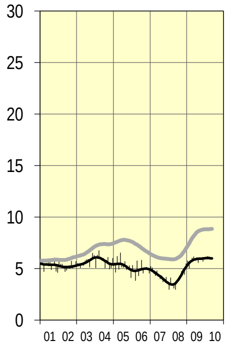
31h. Men 35–44



31i. Men 45–54



31j. Men 55–64



5.4 Spurious correlations and disturbing factors

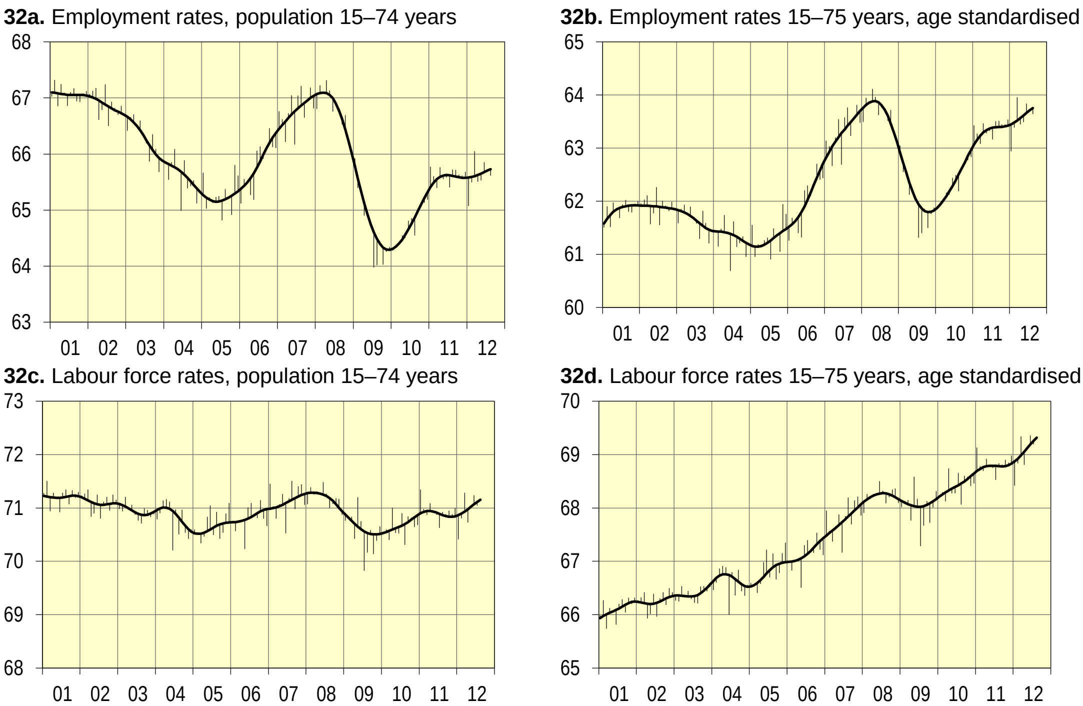
There is always a risk that tables are published that show patterns that are disturbed by a factor that the table has not taken into account. If we publish y by x_1 and x_2 in a two-way table, the correlations indicated by the table can be spurious, i.e. generated by a third explanatory variable x_3.

If we e.g. publish a table with unemployment rates by sex and age, the most important explanation of unemployment can be level of education. That factor can be correlated with age and this will give a spurious correlation between age and unemployment in our two-way table. The solution is to control for education by creating a three-way table. We can also compare age groups by standardising for education so that standardised unemployment rates are computed, where each age group gets the same distribution of the different levels of education.

The same problem can also disturb time series data. The population for the LFS is persons 15–74 years. However, the age distribution can change as a result of baby-boom effects. This is the case in Chart 32. During the period 2001–2012, persons born during the 1940s entered the oldest age group in the LFS and that disturbed the series regarding employment rates and labour force rates.

Chart 32a shows employment rates where the changing age distribution is not controlled. In Chart 32b the employment rates for each age group have been combined with the same standardised weights used each month. In this way the changing age distribution will not disturb. Instead of a negative long-term trend as in Chart 32a, we see a positive long-term trend. The same holds for the labour force rates in charts 32c and 32d. Chart 32c shows a negative long-term trend, but that is a spurious correlation. The negative trend is due to the changing age distribution. When we standardise for age, the long-term trend becomes positive in Chart 32d.

Chart 32. Negative long-term trends become positive when rates are age standardised



References

Elezovic S., Odencrants M. and Xie Y. (2009): *Summakonsistent säsongrensning 1 and 2.* Project reports (in Swedish), Statistics Sweden.

Eurostat (2009): *ESS Guidelines on Seasonal Adjustment.*

Statistics Canada (2009): *Quality Guidelines*. Fifth Edition – October 2009.

Statistics Sweden (2012): *Actual Hours Worked in the Swedish LFS* Background Facts – Labour and Education Statistics 2012:1.

Stuckey A., Zhang and X. and McLaren C. (2004): *Aggregation of Seasonally Adjusted Estimates by a Post-Adjustment.* Australian Bureau of Statistics, 2004.

Wallgren A., Wallgren B., Persson R., Jorner U., Haaland J. (1996): *Graphing Statistics & Data – Creating Better Charts.* SAGE Publications, Inc.

Wallgren A., Wallgren B. (2007): *Register-based Statistics – Administrative Data for Statistical Purposes.* John Wiley & Sons Ltd, Chichester, England.

Wallgren A., Wallgren B. (2012): *Linking a system of time series – Recalculation of Labour Force Surveys 1987–1992.* Methodology reports from Statistics Sweden 2012:2.

Wallgren A., Wallgren B. (2013): *Revising Surveys – Linking Old and New Data.* Background Facts – Labour and Education Statistics 2013:2.

2007:1 Några väsentliga sysselsättningsbegrepp i den officiella statistiken

2007:2 Registerbaserad aktivitetsstatistik

2008:1 Ungdomar utan fullföljd gymnasieutbildning – en undersökning med många utmaningar

2009:1 Longitudinell Integrationsdatabas för Sjukförsäkrings- och Arbetsmarknadsstudier (LISA) 1990–2007

2010:1 Principiella grunder för Arbetskraftsundersökningarna (AKU) och arbetsmarknadsstatistiken

2010:2 Rekryteringsstatistik från AKU

2011:1 Basic principles for Labour Force Surveys (LFS) and labour market statistics

2011:2 Recruitment Statistics for the Swedish Labour Force Survey

2011:3 Arbetskraftsundersökningarna (AKU) 50 år. Fyra forskarperspektiv på arbetsmarknaden

2011:4 Longitudinell integrationsdatabas för Sjukförsäkrings- och Arbetsmarknadsstudier (LISA) 1990–2009

2011:5 Yrkesregistret med yrkesstatistik. En beskrivning av innehåll och kvalitet

2011:6 Urvals- och estimationsförfarandet i de svenska arbetskraftsundersökningarna (AKU)

2011:7 Konjunkturberoende i inflödet till och utflödet från högre studier

2012:1 Actual Hours Worked in the Swedish LFS. Four articles

2013:1 Ungdomsarbetslöshet – jämförbarhet i statistiken mellan ett antal europeiska länder

2013:2 Revising Surveys – Linking Old and New Data

ISSN 1654-465X (Online)