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Book

Break estimation in the Norwegian LFS due to the 2021 redesign : documentation of the methods and some results

Statistisk sentralbyrå
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Documentation of the methods and some results

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Preface

This report from Statistics Norway is based on the final methodology report of our project regarding assessing the impact of the break in time series due to the introduction of the IESS FR as regards the comparability for employment and unemployment data funded by Eurostat, under Grant agreement: 826605 – 2018-NO-LFS-QUALITY BREAKS

The work has been a collaboration project with participants from three departments at Statistics Norway. The Project group have consisted of (the administrative leader) Ole Sandvik from Division for labour market and wage statistics; from the Research department Håvard Hungnes, Unit for macroeconomics and Terje Skjerpen, Unit for environmental, resource and innovation economics; and Xiaoming Chen Jansen, Dinh Quang Pham and Jørn Ivar Hamre from the Division for methods.

Many thanks to professor Jan van den Brakel from Maastricht University and Statistics Netherland for his study visit to Statistics Norway. He has contributed with important insight to measuring and adjusting for redesign effects in repeated surveys through his lectures and seminars, and inspired us for our further work.

Thanks to Melike Oguz-Alper for proposing the method for adjustment factor for wave-adjusted monthly LFS-series. Also, thanks to Susie Jentoft and Ole Richard Storberget Villund for work on the sampling design and weighting procedure for the parallel data collection 2020Q4, from which this project has benefited.

Statistisk sentralbyrå, 22.01.2022

Arvid Olav Lysø

Abstract

In 2021 The Norwegian Labour force survey (LFS) went through a substantial redesign in accordance with the new regulation for integrated European social statistics (IESS). To ensure coherent labour market time series for the main indicators, the redesign's impact is modelled to make back-calculated estimates adjusted for possible breaks due to the 2021 LFS-redesign.

We pursue a structural time series approach in the tradition of Pfeffermann (1991), van den Brakel et al. (2009, 2015) and Elliott and Zong (2019). Breaks are estimated for the number of employed and unemployed persons.

In addition to the 8 waves with monthly LFS data for employed and unemployed persons, we also include auxiliary time series for registered number of employees and unemployed, respectively, in the preferred models.

The structural time series model contains unobserved components for trend, seasonality and irregularity, all of which are assumed to be the same for all waves. A smooth trend model is used. In addition, we account for rotation group bias and the autocorrelation structure brought about by the rotating panel design, as well as sampling error heterogeneity caused by changes in the (net) sample sizes over time.

The auxiliary time series are decomposed into components for trend, seasonality and irregularity. Information from the auxiliary variables is used to obtain more precise break estimates by allowing the two trend components' error terms to be correlated.

To correct for the effect of the COVID-19 pandemic, we allow the hyperparameters for the trend to be higher during the pandemic. We do this to counteract the contaminating effects the pandemic has on the estimate of the structural break following the redesign of the LFS.

The effect of the redesign is modelled as separate level shifts for each wave. The final break estimates are based on modelling time series from 2006M1-2021M10. Information from a parallel survey with the new questionnaire carried out in the last quarter of 2020 for a small sample is also utilized in the time series model.

The time series are modelled for four main domains: gender cross-classified by age 24 and below / 25 and above. The domain-specific break estimates are given as the average of the estimates of the break parameters for the 8 waves. These break estimates are divided into sub-groups using monthly time-varying sub-group splitting factors assuming a proportional distribution of the breaks.

We find a positive break estimate of about 22,000 employed and 5,000 unemployed persons aged 15-74, but only the break estimate for employed persons is significant.

The break estimates relative to the population are used to produce back-calculated monthly and quarterly time series for main indicators for the years 2006-2020.

Contents

1. Introduction

Time series from the labour force surveys (LFS) that describe the situation in the labour market are important for many users. Therefore, these time series must be defined consistently across time; otherwise, it is hard to interpret them. From time to time, it is necessary to redesign the surveys, for instance in conjunction with international regulations. Such changes require correction of time series to make them comparable over time. How to best quantify and implement such corrections depends on the information at hand, for instance whether one has parallel surveys or auxiliary variables to one's disposition.

In 2021 the Norwegian LFS has gone through a substantial redesign in accordance with the new regulation for integrated European social statistics (IESS). There is a new modified questionnaire, where question sequences, question formulations and answer alternatives have changed. The target population was also changed from covering all registered residents aged 15-74 to registered residents aged 15-89 in private households. We used this opportunity to change the sampling design (gradually for each new wave). The sampling unit changes from nuclear family to person, and the sample is now stratified according to the characteristics of the persons. Due to the change of the sampling unit, we do not allow other family or registered household members to answer on behalf of the person any more.

We document work related to corrections of breaks in the main LFS time series brought about by a substantial redesign of the Norwegian LFS from the beginning of 2021. The analysis is carried out within a structural time series framework using state space models on monthly data from 2006M1 to 2021M10. We follow the tradition introduced by Pfeffermann (1991) and further developed by ,e.g., van den Brakel et al. (2009, 2015) and Elliott and Zong (2019).The Norwegian LFSs follows a rotating design, where each respondent basically participates 8 times over a two-year period. The modelling strategy follows a disaggregated approach in that the modelling takes place at domains and numbers for the aggregate are derived from this disaggregated information. Using this approach accounts for the fact that the different domains are heterogeneous, which again influences aggregate behaviour. We distinguish between employed and unemployed individuals, and model time series for both employed and unemployed persons . Besides the wave information, we also utilize auxiliary information from registers. This auxiliary information is essential for identifying the effect of the redesign of the LFS, since the redesign does not influence the register data. We use one auxiliary variable in conjunction with each (sub-)estimation. Thus, we typically consider modelling a vector with 9 elements, where the eight first are from the LFS, and the last one is from the register.

The modelled time series depends on different components. The time series for the eight waves are assumed to share a common trend component, a common seasonal component and a common irregular component. The auxiliary time series has its own trend, seasonal and irregular component. The two trends components are assumed to be smooth (i.e., a restricted version of the local linear trend specification). We allow for correlation between the two trend components. This assumption is essential, because this is the only channel through which the auxiliary variables influence what estimated hyperparameters and extracted components one ends up with for the time series from the LFS. The correlation must be sizeable, which luckily seems to be the conclusion from the empirical analysis.

For the time series from the LFS, additional components are added to the model specification. First, we allow for rotation group bias (RGB). In contrast to CBS that (for the Netherlands) uses the RGB to benchmark their time series levels to the first wave, see van den Brakel and Krieg (2009, 2015), we follow e.g. Elliott and Zong (2019) to specify the RGB component such that the LFS series is the average of all of the waves. However, in contrast to Elliott and Zong (2019), we do this in a symmetric way where we do not treat one wave as residual and thereby put less weight on this wave. Second, we account for autocorrelation in survey errors stemming from the design of the survey. We pre-estimate the autocorrelation parameters using SURE models and plug them into the overall model.

The break effects are modelled using levels shift dummies. We allow the breaks to vary across the waves. Our focus is on the break at the beginning of 2021.

We also carry through calculations using information from a small parallel survey in the last quarter of 2020. This parallel survey produces a priori information that can be used in the time series model. Technically, the time-invariant parameters related to the break are incorporated in the state vector. Whereas the break parameters related to waves 2-8 are initialized with a diffuse prior, the break parameter related to wave 1 is initialized exactly by utilizing information from the parallel survey.

The ongoing COVID-19 pandemic has made it more challenging to estimate the effect of the new design. We have followed the suggestion by van den Brakel et al. (2021) to temporarily operate with higher hyperparameters for the trend to counteract the effect of the shock represented by the pandemic.

Apart from the pre-estimation of the autocorrelation parameters occurring in the survey error module, all other inference has been carried out using the r-package KFAS,[1] see Helske (2017).

As for the specification of the model underlying the estimation of the autocorrelation parameters related to the survey error component, we have put weight on having a simple model with rather few hyperparameters involved. Modelling the two trend components involves only three hyperparameters, and the two trigonometric seasonal components involve only two parameters. Also, the RGB component involves only one variance.

The models are estimated on monthly data stretching from 2006M1 to 2021M10. The break estimates vary somewhat across the four domains that we consider and which subsequent constitutes the basis for the total series.

Based on the obtained break estimates, we carry out further calculations. First, we adjust the whole time series back to its start in 2006M1. Since the model specification is based on untransformed variables, we generate break effects in the pre-break period by calculating break factors, implicitly saying that the size of the break constitutes the same share (of the population in that domain) as in the break period. The four domains mentioned above can be further disaggregated. We also have a break adjustment procedure for these even more disaggregated time series.

The rest of this report is organized the following way. The specification of time-series models is the topic for Section 2. We explicitly specify the state space model used for estimation. This section also covers how we handle the redesign of the survey and how we account for the effects of the COVID-19 pandemic. Section 3 is about the data construction and information about the design of the Norwegian LFS. This section describes how the monthly wave series are constructed to obtain numbers at the population level. Furthermore, the section comments on the underlying redesign of the survey in 2021. Finally, this section also informs about the register data used, including how it is prepared. In Section 4, we report our empirical results. Even though our main concern is the estimates of the parameters corresponding to the effect of the redesign, we are also interested in the estimates of the hyperparameters involved for the other components of the model. Section 5 shows how sub-group break estimates are calculated and used for back-calculating to obtain break adjusted series. Section 6 looks at how an adjustment of the time series model can be used to

[1] https://CRAN.R-project.org/package=KFAS, Version 1.4.6

produce monthly LFS-trend estimates and compare them with seasonal- and break adjusted monthly figures.

Some details are located in various annexes. These annexes include a description of how we account for survey errors, the model diagnostics we apply, and issues related to robustness. In the annexes, we also present some preliminary results and information about a parallel data collection undertaken in 2020Q4 and how it is used here. Finally, we include an annex with a more extended methodological summary, sent to Eurostat for publication at their website Statistics Explained.[2]

[2] https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey_-_correction_for_breaks_in_time_series&stable=0&redirect=no#Input_for_break_correction

2. Time series model for estimating possible overall breaks due to the 2021 LFS-redesign

In the Norwegian LFS survey, the interviewees are interviewed for eight consecutive quarters. In each quarter, 1/8 of the sample leaves the survey at the same time as new interviewees corresponding to 1/8 of the sample are included in the survey for the first time. Interviewees participating in the survey for the first time belong to wave 1, those interviewed for the second time constitute wave 2, and so on. Those interviewed for the last time thus constitute wave 8. We take advantage of the fact that these waves must follow the same trend and have the same seasonal pattern and that they have an autocorrelated component because of the survey design. Bailar (1975) and Pfeffermann (1991) describe this type of model.

2.1. State-space model of the Norwegian LFS

Here, in our presentation of the model, we will primarily refer to it as the model for LFS unemployment. However, this is purely to simplify the exposition. The model for LFS employment is identical. We define y_t^i , where $i = 1,2, \dots ,8$, as the unemployment estimate (or the employment estimate) based on the observations in wave *i* of the LFS survey.[3] Furthermore, let $Y_t = (y_t^1, y_t^2, \dots , y_t^8)'$ be a vector of the estimates from all 8 waves. The model we use as a starting point is

(1) $$Y_t = 1_8\theta_t + \lambda_t + e_t,$$

where 1_8 is a column vector of 8 ones, θ_t is an estimate of the "true" LFS unemployment, the vector $\lambda_t = (\lambda_t^1, \lambda_t^2, \dots , \lambda_t^8)'$ represents the time-varying rotation group bias with $\sum_{i=1}^{8} \lambda_t^i = 0$, and $e_t = (e_t^1, e_t^2, \dots , e_t^8)'$ is a vector of wave-specific survey errors. Furthermore, the "true" unemployment can be decomposed as

(2) $$\theta_t = L_t + S_t + I_t,$$

where L_t is the level, S_t represents the season, and I_t is the irregular component. All these components are common to the 8 waves.

Generally, the level is often assumed to follow a local level model, a local linear trend model, or a smooth trend model; see Durbin et al. (2001). The local linear trend model is given as

(3) $$\begin{aligned} L_t &= L_{t-1} + R_{t-1} + w_t^L, & w_t^L &\sim \mathrm{N}(0, \sigma_L^2) \\ R_t &= R_{t-1} + w_t^R, & w_t^R &\sim \mathrm{N}(0, \sigma_R^2) \end{aligned}$$

If $\sigma_R^2 = 0$ and $R_0 = 0$, then (3) simplifies to the local level model. If $\sigma_L^2 = 0$ instead, (3) simplifies to the smooth trend model. If both $\sigma_L^2 = 0$ and $\sigma_R^2 = 0$, then L_t is following a deterministic trend given by R_0, or it is just a constant if $R_0 = 0$.

The seasonal component, S_t, is often modelled as a deterministic seasonal model, a dummy seasonal model, or a trigonometric seasonal model; see Durbin and Koopman (2001, Section 3.2). With monthly data, the trigonometric seasonal model is given as

[3] See also Section 3 for how the wave-specific estimate is derived. However, in the presentation here, it is only important that we have a wave-specific estimate. (Here, we also ignore notation that indicates that these figures are estimates.)

(4) $S_t = \sum_{j=1}^{6} \gamma_{j,t}$

$$\gamma_{j,t} = \gamma_{j,t-1} \cos(\pi j/6) + \gamma^*_{j,t-1} \sin(\pi j/6) + \omega_{j,t} \quad \omega_{j,t} \sim N(0, \sigma^2_\omega)$$

$$\gamma^*_{j,t} = \gamma^*_{j,t-1} \cos(\pi j/6) + \gamma_{j,t-1} \sin(\pi j/6) + \omega^*_{j,t} \quad \omega^*_{j,t} \sim N(0, \sigma^2_\omega) \;\; j = 1,2,\ldots,6.$$

We note that here this process depends on only one hyperparameter, as the variance σ^2_ω is common for all disturbance terms. The use of one common variance is also imposed in our implementation.[4]

The irregular component I_t is assumed to be white noise, independent and identical distributed:

(5) $I_t \sim \mathrm{N}(0, \sigma^2_I)$.

For both the level and the parameters in λ_t to be identifiable, a restriction must be imposed. We apply the restriction $1'_8\lambda_t = 0$. This restriction is usually imposed by restricting one of the parameters in λ_t, for example, the last one, to be equal to the negative of the sum of the others, and let the remaining ones follow random walks (see, e.g., Elliot and Zong, 2019). However, this will often lead to a large variance in the rotation group bias for the wave that secures that the restriction holds. Therefore, we find it more suitable to apply the symmetric approach;

(6) $\lambda_t = \lambda_{t-1} + \eta_t \qquad \eta_t \sim N\left(0_8, \left(I_8 - \frac{1}{8} 1_{8\times 8}\right) \sigma^2_\lambda\right)$,

where I_8 is the identity matrix of size 8, and $1_{8\times 8}$ is an 8 times 8 matrix with each element equal to 1. The formulation in (6) secures that $1'_8\lambda_t = 0$ if $1'_8\lambda_0 = 0$ (i.e., if the initial values of the process also satisfy the restriction). The representation in (6) is similar to some representations that have been used for seasonal effects; see, e.g., Harvey (2006).

The interviewees in the first wave are interviewed for the first time, whereas the interviewees in the other waves have been interviewed before. The variance for the wave-specific survey errors is also time-dependent, partly due to variation in the number of people interviewed each month. Let $K^j_t = \sqrt{\widehat{Var}[\hat{Y}^j_d]}$ be an an estimate of the standard error of the survey error, see Section 3. The survey errors are modelled as:

(7) $e^j_t = K^j_t \; \tilde{e}^j_t \qquad$ where $\tilde{e}^1_t = \varepsilon^1_t$ and $\tilde{e}^j_t = \phi \; \tilde{e}^{j-1}_{t-3} + \varepsilon^j_t$ with $\varepsilon^j_t \sim N(0, \sigma^2_{e_i})$).

If K^j_t is a good estimate of the standard error of the survey error, $\tilde{e}^j_t$ will have an estimated variance close to one. We will not impose that here, as K^j_t might not be a good estimate of the standard error of the survey error. However, we impose that $Var(\tilde{e}^2_t) =\ldots= Var(\tilde{e}^8_t)$, from which it follows that $\sigma^2_{e_2} = \sigma^2_{e_3} =\ldots= \sigma^2_{e_8}$, which is a restriction we impose on the system.[5]

2.2. Break and auxiliary variables

We now extend our model to allow for a possible break following Harvey and Durbin (1986). By including a break, (1) changes to

(1′) $Y_t = 1_8\theta_t + \lambda_t + \Delta_t\beta + e_t$.

[4] Note that π here is not a parameter but the ratio of a circle's circumference to its diameter (approximately 3.14).
[5] It also follows that $\sigma^2_{e_1} = \sigma^2_{e_2}/(1-\phi^2)$, so we could also impose this restriction on the variance of the survey error in the first wave. However, this restriction depends on a good estimate of ϕ, so to account for that our estimate of ϕ might be biased, we do not impose this restriction.

In (1'), $\Delta_t = \mathrm{Diag}(\delta_t^1, \delta_t^2, \ldots, \delta_t^8)$, is a diagonal matrix with dummy variables that change from zero to one at the time of the possible break (for example, when the calibration changes from an old to a new source, or the survey changes from an old to a new design). The 8-dimensional vector with regression coefficients, $\beta = (\beta^1, \beta^2, \ldots, \beta^8)'$represents the size of the break for each of the waves. In our situation, when considering the break due to the new LFS questionnaire from 2021, the break occurs simultaneously for all the waves. Thus, $\Delta_t = 1_{t\geq 2021\mathrm{m}01} I_8$.[6,7]

We include auxiliary variables in the model to improve the estimates for the discontinuities. Consider X_t as such a variable (e.g., unemployment from a register, or employment from a register):

$$X_t = \theta_t^X = L_t^X + S_t^X + I_t^X, \tag{8}$$

where L_t^X, S_t^X, I_t^X are vector versions of the level, seasonal, and irregular components. These are modelled similarly to these components for the LFS variables in (3)-(5). van den Brakel and Krieg (2015) suggest constructing a model where the vectors Y_t and X_t are modelled jointly. This joint system can be formulated as

$$\begin{pmatrix} y_t^1 \\ y_t^2 \\ y_t^3 \\ y_t^4 \\ y_t^5 \\ y_t^6 \\ y_t^7 \\ y_t^8 \\ X_t \end{pmatrix} = \begin{pmatrix} \mathbf{1}_8 \theta_t^{LFS} \\ \theta_t^X \end{pmatrix} + \begin{pmatrix} \lambda_t^1 \\ \lambda_t^2 \\ \lambda_t^3 \\ \lambda_t^4 \\ \lambda_t^5 \\ \lambda_t^6 \\ \lambda_t^7 \\ \lambda_t^8 \\ 0 \end{pmatrix} + \begin{pmatrix} \beta_{21}^1 \\ \beta_{21}^2 \\ \beta_{21}^3 \\ \beta_{21}^4 \\ \beta_{21}^5 \\ \beta_{21}^6 \\ \beta_{21}^7 \\ \beta_{21}^8 \\ 0 \end{pmatrix} 1_{t\geq 2021\mathrm{m}01} + \begin{pmatrix} e_t^1 \\ e_t^2 \\ e_t^3 \\ e_t^4 \\ e_t^5 \\ e_t^6 \\ e_t^7 \\ e_t^8 \\ 0 \end{pmatrix} \tag{9}$$

For it to be an advantage to jointly model the LFS variable (LFS unemployment) and the register variable, there must be a correlation between these. We can have this correlation in level, season or irregular component.

$$\begin{aligned} &Cov(w_t^{L,\,LFS}, w_t^{L,X}) = \sigma_{L,LFS\_X}^2 && \text{(trend-level)} \\ &Cov(w_t^{R,\,LFS}, w_t^{R,X}) = \sigma_{R,LFS\_X}^2 && \text{(trend-slope)} \\ &\mathrm{Cov}(\omega_{j,t}^{L,\,LFS}, \omega_{j,t}^{L,X}) = \sigma_{S,LFS_X}^2, && \text{(season)} \\ &Cov(I_t^{LFS}, I_t^X) = \sigma_{R,LFS\_X}^2 && \text{(irregular component)} \end{aligned} \tag{10}$$

2.3. Larger fluctuation in the trend during COVID-19

The COVID-19 pandemic led to large fluctuations in the labour market. The model we have laid out above does not allow for larger fluctuations in the labour market. The break estimate can be severely biased without considering this increased variation in the LFS and register time series.

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[6] However, if we redefine the break as having the value -1 prior to the break date and 0 for the break date and thereafter, the results would not be altered.

[7] In the estimation we have also included a break in 2015M1. This break account for possible level shift due to a less informative auxiliary register variable before 2015 applied in the weighting procedure of the LFS. From 2015 we got the new high-quality A-Scheme register which is a monthly pay-slip register to the Tax authorities. Up to 2014 we had the Aa-register of change notifications (with delays) regarding hiring and firing from employers to Social Security.

In our modelling, we use the smooth trend model, i.e., $\sigma_L^2 = 0$ in (3). To simplify, we maintain this assumption when describing the modification of the state-space model to allow for larger fluctuations in parts of our sample.

(3’) $$L_t = L_{t-1} + R_{t-1},$$

$$R_t = R_{t-1} + \Psi_t^{1/2} w_t^R, \qquad w_t^R \sim \mathrm{N}(0, \sigma_R^2)$$

A similar trend modification is also applied in van den Brakel et al. (2021). The formulation in (3’) implies that the variance of the slope is time-varying and given by $\Psi_t \sigma_R^2$.

2.4. State-space representation

To estimate the model above, we specify it in state-space form. Let $\boldsymbol{y}_t = (y_t^1, y_t^2, \ldots, y_t^8, X_t)'$ be the vector of all 8 waves of the LFS variable plus an auxiliary variable. The measurement equation for our implementation is

(11) $$\boldsymbol{y_t} = \boldsymbol{Z_t}\boldsymbol{\alpha_t},$$

where $\boldsymbol{\alpha_t}$, is a vector of unobserved components for level (*R* and *L*), season (γ and γ^*), irregular component (*I*), rotation group bias (the λ’s), components for survey errors ($\tilde{e}_s^j$, for $j = 1,2, \ldots, 8$ and $s = t, t-1, t-2$) for the LFS variables. In addition, it includes similar components for level, season and the irregular part for the auxiliary variable. Finally, the break coefficients for all LFS waves are included in $\boldsymbol{\alpha_t}$. The coefficient matrix $\boldsymbol{Z_t}$ contains only known parameters, primarily 0 and 1, but also $cos(\pi j/6)$, $sin(\pi j/6)$, and K_t^j. In addition to including the time-dependent variables K_t^j, $\boldsymbol{Z_t}$ is also time-dependent as it includes the break-variable $1_{t \geq 2021M01}$.

The transition equation is given by

(12) $$\boldsymbol{\alpha_{t+1}} = \boldsymbol{T}\boldsymbol{\alpha_t} + \boldsymbol{G_t}\boldsymbol{\nu_t}, \quad \text{with} \quad \boldsymbol{\nu_t} \sim N(\boldsymbol{0}, \boldsymbol{\Omega}),$$

where the transformation matrix *T* contains mostly 0 and 1, but also the autocorrelation parameter ϕ. The vector $\boldsymbol{\nu_t}$, contains error terms. Finally, the selection matrix $\boldsymbol{G_t}$ contains mostly 0 and 1, but also $\Psi_t^{1/2}$.

The initial expectation vector and covariance matrix of the state vector is given by

(13) $$\boldsymbol{\alpha_1} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma}).$$

We use diffuse initialising for most of the variables (see e.g., Koopman,1997 and Koopman and Durbin, 2000). In (13), this implies setting the corresponding element in $\boldsymbol{\Sigma}$ equal to infinity. For the break coefficients, we use diffuse initialization for waves 2-8. For wave 1, we can use diffuse initialization. However, if we want to use prior information for this break, such as from a parallel run of the questioner for this wave, we can use this as an informative prior.

2.5. Estimation

State-space models can be challenging to estimate, and good starting values are essential. Applying the most general version of the model laid out above requires many parameters to be estimated. To reduce the estimation problem, we have included several parameter restrictions:

(i) We use a smooth trend for both the LFS and register variables. This reduces the number of estimated parameters by 3, as we do not need to estimate the 2 hyperparameters for the level variance for the two sets of variables and one covariance between them. A smooth trend is also widely used, also applied to the LFS (see van den Brakel and Krieg (2009, 2015).

(ii) We have restricted the 12 hyperparameters for variance in the seasonal component to be equal, both for the LFS and the register variables.[8] We also ignore the potential correlation between the seasonal component for the LFS variable and the register variable.

(iii) We ignore the potential covariance between the irregular components for the LFS variable and the register variable.

(iv) We impose the same variance for all 8 waves for the rotation group bias.

(v) For the survey errors for each wave, we restrict 7 of them to have equal variance; see also above.

Following Pfefferman et al. (1998), we estimate the autocorrelation coefficient in a separate system; see Annex A. By doing so, we can treat it as “known” when estimating the remaining parameters of the state-space model.

Finally, for Ψ_t, we applied two types of simplifications.

First, we use the same value for this for the LFS variable and the register variable, $\Psi_t^{\mathrm{LFS}} = \Psi_t^{\mathrm{R}}$. Therefore, we apply the notation Ψ_t, i.e., without superscript.

Second, we have divided our sample into three parts. The first part is the pre-corona part, defined as the period up to 2019M12. In this period, we apply $\Psi_t = 1$, such that σ_R^2 is the variance for the slope in the pre-corona period. The second part is the initial shut-down part of the COVID-19 pandemic, with large fluctuations in labour force figures. This period is assumed to cover the first half of 2020, i.e., 2020M1-2020M6. Let us restrict Ψ_t to take the same value in all months in this period, i.e. $\Psi_t = \Psi_A$ for $t = 2020M1, 2020M2, \ldots, 2020M6$. The last part, the recovering period, starts in mid-2020. There are still larger than usual fluctuations in this period than before the coronavirus (COVID-19) crises, but not as large as when the pandemic first hit the Norwegian economy. Also, in this period, which lasts the remaining of our sample, we restrict Ψ_t to take the same value in all months, i.e. $\Psi_t = \Psi_B$ for $t = 2020M7, 2020M8, \ldots, 2021M10$. In many of the tables and figures, we use the terms *K1* and *K2* instead, where $K1 = \Psi_A \text{ and } K2 = \Psi_B$.

Third, we apply a grid search technique to estimate Ψ_A and Ψ_B. We construct a two-dimensional grid for Ψ_A and Ψ_B (where $1 \leq \Psi_A \leq \Psi_B$). For each pair of values for Ψ_A and Ψ_B, we estimate the remaining parameters in the state-space model and calculate the likelihood value. The estimates of Ψ_A and Ψ_B are given by the pair of values that lead to the highest likelihood value.[9] The final estimates of the remaining values are conditioned on this pair of values for Ψ_A and Ψ_B.

2.6. Diagnostics

Various diagnostics are available to evaluate the performance of structural time series models estimated within a state space framework; see, for instance, Harvey and Koopman (1992). We concentrate on graphs displaying standardized recursive residuals (standardized one-step-ahead prediction errors). Due to modelling of a level shift in 2015, these are only depicted after 2015. Furthermore, we include auxiliary residuals related to the slope component of the trend and the irregular component. Without correcting the hyperparameters related to the trend components

[8] Although this restriction is common for trigonometric season model, it is not always applied. In KFAS, this restriction is not directly imposed when applying the trigonometric season model.

[9] After trying out a couple of different versions of the grid, we ended up with using the following crude grid values in our search: Ψ_A= 16, 25 or 49 and Ψ_B= (Ψ_A + L-1) / L, where L=2, 4, 6, 8, 12, 24 or 48. See also Appendix C.

because of the COVID-19 pandemic, the residuals mentioned above performed rather badly, and are not reported. In Annex B, we report the residuals for the models with time-varying hyperparameters for the trend during the COVID-19 pandemic. The residuals in this “optimal” model seem to behave quite well.

3. About the data

3.1. The Norwegian Labour Force Survey (LFS)

The Norwegian labour force survey (LFS) measures key labour market indicators in the population, such as employment and unemployment. The data collection is carried out by telephone interviews only.

The sampling design before 2021

The Norwegian LFS has a rotating panel design where the same selected people are requested to respond over several quarters. Since 1996, participants have been requested to respond every 3 months, a total of 8 times over a two-year period (8 consecutive quarters). This achieves good accuracy for 3-months average level estimates and for change-estimates between two following (but non-overlapping) 3-months moving averages.[10] However, it is not ideal for estimating pure monthly figures and change-estimates from the previous month, as there is no overlap of persons in the sample between neighbouring months.

Sampling frames for our LFS have always been created from our central population register (CPR), but the sampling unit, stratification and allocation have changed over time. However, the interview unit and the main outcome indicators for the LFS still relate to individual persons.

Before 2021, the sample was selected from a nuclear family[11] sampling frame, stratified by county of residence.[12] Lesser populated counties were disproportionately overrepresented before 2021.[13]

New sampling designs gradually phased in from 2021Q1

The target population from 2021 is persons resident in private households, even though only information for persons aged 15-74 is utilized. The sampling unit is now person, and a stratified random sample of 2,625 persons are selected and rotated in every quarter (for their first interview, called wave 1), while about 3,000 persons from the old design are rolled out after 8 quarters of participation (wave 8 in the previous quarter). This means that the main sample used for quarterly LFS gradually decreases to about 21,000 persons by the 4th quarter of 2022. This reduction in the primary sample is undertaken to make room for the interviewing of all household members in the

[10] The rotation pattern, termed monthly 1-2-1(8), and its efficiency is discussed in Steel and McLaren (2009).

[11] The family concept in the Norwegian CPR is not the same as the family concept used by ESS and Eurostat since it includes individuals living alone. According to the family definition in the CPR a family can consist of members from maximum 2 generations. A reference person is defined (the male in the parent generation, possibly a female if no male exists) in every family, and the unique personal ID number to the reference person is used as the family ID number. The definition of nuclear family includes the following types of families: single persons, married couples without children, married couples and their children and single parent who live with child(ren), see Hamre and Heldal (2013). Due to quality issues regarding the sampling unit, cohabitants were never regarded as a family unit (with same family ID number) in the old system for selecting the LFS sample, unlike Statistics Norway's statistics on families (https://www.ssb.no/en/befolkning/barn-familier-og-husholdninger/statistikk/familier-og-husholdninger).

[12] In 2020 the Norwegian NUTS3-regions was reduced from 18 to 11 counties and our NUTS2-regions changed as well in our Regional reform. Therefore, our sampling design had to be adjusted a little. For the quarterly updating of our LFS-sample from 2020Q2 to 2020Q4 , the sampling unit, stratification variable (current version of the NUTS3-regions) and sample size were unchanged. The least possible change of the allocation of the sample was made to minimize the risk of any break in the main figures for this short intermediate but turbulent period until the 2021 redesign. This change in allocation was implemented by using population-weighted average of the previous over/under sampling rates in the counties. For information about the classification of new Norwegian NUTS2 and NUTS3 regions valid from January 2020 (and the change from its previous version) please see: https://www.ssb.no/en/klass/klassifikasjoner/104 and https://www.ssb.no/en/klass/klassifikasjoner/106

[13] For information about the old sampling proportions in different counties, see Table 3.1 in Hamre and Heldal (2013).

second wave, called household subsampling. By the 4th quarter of 2022, we stipulate that the total sample size will be around 24,000 persons each quarter, including the household subsample.[14]

Stratification by person-characteristics is used. The following 56 combinations of age groups, region and register-based employment status is used:

- Each of the 6 NUTS2 regions[15] for register-unemployed 15-74, and
- NUTS2 regions cross-classified by the age groups (15-24, 25-54, 55-66, 67-74) and by register status (employees, others except for register-unemployed)
- Two extra strata for persons aged 75-89; one for register-employees and one for other[16]

Allocation of the new sample is based on previous work[17] and have used an optimal, multivariate allocation described in Bethel (1989).[18] We first allocate the sample to fulfil the EU requirements[19] and then fill up the remaining sample to maximize precision for the unemployment nationally.

This stratification on person-characteristics and optimal allocation of the sample gives better precision for the total unemployment figures that more than offset the effects of the reduced sample size. For other variables or subgroups, the adverse effect of reduced sample size is probably dominant.

The estimation procedure

The estimation procedure for the Norwegian LFS is a one-step multiple model-calibration (mmc) based on monthly LFS-data and register data. The method uses register data for employment status, age, sex, NUTS2-regions and immigration background directly, and register information on education level, family size, and marital status indirectly. The method is described further in Oguz-Alper (2018); see also Nguyen and Zhang (2020).

As from 2021, the estimation procedure is adjusted somewhat, taking into account the new population delimitation,[20] our new NUTS2 regions, and adjusting initial weights taking into account that different persons in different waves have been selected from different sampling designs.

The most important changes in the 2021-redesign of the Norwegian LFS and conditions that can cause breaks

The target population was changed from covering all registered residents aged 15-74 to registered residents aged 15-89 in private households according to our new household register. This means that more age groups are included, while, for example, persons enrolled in compulsory military service are excluded from the target population. Earlier, persons enrolled in compulsory military service were part of the target population for the Norwegian LFS survey: if they were sampled for the LFS and answered accordingly (possibly through proxy interviewing), they were classified as employed. On the other hand, excluding persons registered resident in institutions (non-private

[14] In the meantime, the sample size including the household sub-sample unfortunately will be somewhat larger in order to have a smooth transition of sampling designs.
[15] For information about the classification of new Norwegian NUTS2 regions valid from January 2020, please see: https://www.ssb.no/en/klass/klassifikasjoner/106/koder
[16] In addition, the sample include persons bellow age 15 and above 89 related to the selected reference persons and an extra sample of persons above 89, but none of them are interviewed. The purpose is to include demographic (register) information about the of the structure of the whole (indirectly selected) household and weighted population figures for the total target population not limited by age.
[17] See Hamre and Jentoft (2019).
[18] The R-package MAUSS-R (Multivariate Allocation of Units in Sampling Surveys) is used. It is documented in Barcaroli et al. (2015) and developed by the Italian Statistical Bureau (Istat).
[19] According to REGULATION (EU) 2019/1700 OF THE EUROPEAN PARLIAMENT AND OF THE COUNCIL of 10 October 2019.
[20] Excluding persons resident in non-private households according to our new household register.

households) such as persons registered as living in nursing homes often less attached to the labour market may pull in the opposite direction. Earlier, they were part of the LFS-target population in Norway. If they were sampled (through the nuclear family) for the LFS and (possibly through proxy interviewing), they probably would answer to a greater extent that they were outside the labour force than other people with similar characteristics resident in private households.[21]

The sampling design also changed. This change is introduced gradually through 2021 and 2022 as only one-eighth of the sample is replaced every quarter.

The sampling unit changes from nuclear family to person, and the total sample is gradually changing from family sample to person sample stratified according to characteristics of the persons. The changed allocation of the sample will gradually change the standard error for different variables and age groups over a two-year period.

Until the beginning of 2021, people in the same family could answer for other family members. Due to the change of the sampling unit to person, we do not allow other family or register household members to answer on behalf of the person, so from 2021 there are no proxy interviewing. This change may lead to higher non-response, especially for younger people, but this should, to a large extent, be compensated for through weighting. [22]

Key definitions are adjusted in accordance with the new regulation. Examples are definitions of employed, full-time/part-time, underemployed, etc.

In the new questionnaire, several variables have changed in line with changes in the labour market. In addition, question sequences, question formulations and answer alternatives have changed due to modernization of the language, increased coordination internationally and adapted self-filling as a future collection method.

From 2021, involuntarily completely laid off people will have the usual questions about job search and availability in the LFS for more than 90 days, thus potentially being classified as outside the labour force. Previously, individuals completely laid off for more than 90 days were automatically considered unemployed in the Norwegian LFS without being asked about active job search or availability. This change in questionnaire and filter, combined with the fact that the Norwegian labour market at the same time is facing a situation with many involuntarily laid off related to the COVID-19 pandemic, contributes to fewer unemployed people according to our new LFS.

This project handles calculating possible breaks for persons aged 15-74 related to the 2021-redesign of the LFS regarding the main indicators; employment and unemployment. It is only the total effect we are trying to measure here, not partial effects caused by the different sources, which would be even more challenging to measure.

[21] Also, homeless may not be considered as residents in private households according to our registers, and now therefore will to be outside the target population according to the new regulation, while inside the (total) population before. Even though probable nonresponse if sampled before 2021, weighting with auxiliary information regarding register employment, possible marginal attachment to the labour marked to greater extent would have been accounted for.

[22] Quality aspects of proxy interviews were studied in Thomsen and Villund (2011). They conclude that proxy interviews probably result in a better employment rate estimate, and that proxy interviews provide data on some hard-to-reach people who have a labour market situation more similar to that of those not reached at all. However, they do acknowledge, that much can be achieved with good post-stratification. Since this study, the Norwegian LFS has improved its methods for estimation. Zhang, Thomsen and Kleven (2013) concluded that proxy interviewing is helpful in situations where one lacks good auxiliary variables to adjust for the selection bias (into proxy). An issue is whether unemployment is such case in our LFS, where auxiliary variables in the estimation procedure are maybe only moderately helpful, see Oguz-Alper (2018) for a detailed overview.

Justification for changing sampling unit

The choice of using family as the sampling unit dates back to when we used face-to-face interviews also in the LFS. Then, the use of family clusters was important to limit travel costs for the interviewers as they could interview several people at the same address. Because the Norwegian LFS is now conducted using telephone interviewing and as most interviewees have their own cell phone, there are few reasons for choosing families instead of persons as the sampling unit. There are also adverse effects of cluster sampling units because spouses are more similar with respect to e.g. education and connection to the labour market than what random selection of persons provides. The main indicators in the LFS, such as employment, unemployed, etc., are related to the person and not family or household. Therefore, it is most natural to have persons as a sampling unit. On the other hand, indirect interviews are difficult to do with persons as a sampling unit. The response rate also increases via the possibility of indirect interviews. Indirect (telephone) interviews are also cost-saving. Overall, around 15% of the persons in the old sample were interviewed by indirect interviews, and the proportion was larger for young people. With the possible use of web forms (CAWI) in the future and possible cost-savings, indirect interviews is not an alternative, and a family sample is not an advantage. A family sample means that the number of extra household members, which must be added for some questions to all household members at least once, is less than if the person is a sampling unit in the quarterly LFS. The reason is that the family unit is closer to the household unit for most people. In sum, the benefits of using persons as a sampling unit for the national unemployment figures will be greater than the disadvantages. Although we would have to set aside a smaller part of the sample for interviewing other household members if we continued to select families, and the non-response rate is expected to increase more in a stratified sample of persons with effective allocation.

Wave-adjustment for monthly LFS-series

The estimation procedure is not based on calibrating by wave. Therefore, we use adjustment factors to multiply the regular monthly weights with wave-divided monthly figures to be consistent with population figures. The consistency is secured for the domains gender cross-classified by 3 age groups (15-24, 25-54 and 55-74) due to the calibration model. Therefore, it brings about consistent estimates for the domains used in this time series model. Let $\hat{N}_d$ and $\hat{N}_{b,d}$ be the sum of monthly mmc-weights for persons in the net sample in domain *d*, totally and in wave *b*, representatively.

The adjustment factors we apply are;[23]

$$(14) \qquad \frac{N_d}{\hat{N}_{b,d}} = \frac{\hat{N}_d}{\hat{N}_{b,d}} = \frac{\sum_{i\in s_d} w_i}{\sum_{i\in s_d} w_i \delta_{bi}},$$

where w_i is the monthly mmc-weight, $\delta_{bi} = 1$ if person *i* is in wave *b*, otherwise $\delta_{bi} = 0$, and N_d is the population total in domain *d*.

We then get:

$$(15) \qquad \sum_{i\in s_d} w_i \frac{N_d}{\hat{N}_{b,d}} \delta_{b,i} = N_d.$$

Here we have $N_d = \hat{N}_d$ because the mmc-weights guarantee that the calibration gives consistent population figures for each of the 6 domains.

With 8 waves and the gross sample evenly distributed, the factors will vary around 8.

A rough approximate variance estimate for the wave-specific monthly LFS-figures

A rough approximate variance estimate for the wave-specific monthly LFS-figures $\hat{Y}_d^j$ is given by:

[23] Thanks to Melike Oguz-Alper for proposing this adjustment factor.

(16) $Var[\hat{Y}^j] = Var[\sum_d \hat{Y}_d^j] = \sum_d Var[\hat{Y}_d^j]$,

where the index j denotes wave and *d* denotes thedomain, and where

(17) $Var[\hat{Y}_d^j] = N_d^2\, \hat{p}_d\, (1 - \hat{p}_d)/n_d^j$, where

n_d^j is the net LFS sample size in wave *j* in domain *d*,
N_d is the population size in domain *d*, and

$\hat{p}_d = \hat{Y}_d/N_d$ is the estimated/weighted proportion for an LFS variable Y in domain *d* based on information from all 8 waves.[24]

3.2. Register data, harmonization and pre-adjustment for earlier breaks

In the time series model for employed persons according to LFS in a domain, a time series of the number of register employees in the domain is used as an auxiliary variable. Similarly, the time series model for unemployed persons according to LFS in a domain uses an auxiliary register time series for that domain from the unemployed registered at the employment office.

The auxiliary register variable in time series models (to estimate a possible effect of the 2021-redesign of the LFS) needs to be comparable over time and not include breaks, at least at the same time as the 2021-redesign. Since our registers have breaks due to changes in source or changes in legislation, we pre-adjust the register time series in advance using standard regARIMA-functionality in the seasonal adjustment software X-13ARIMA-SEATS.[25]

Register employees from A-Scheme register from 2015 and earlier from Aa-register
In January 2015, the Employee register (Aa-register) was replaced by the new A-Scheme register on monthly reporting of employee and payroll information to the Norwegian Labour and Welfare Administration (NAV), the Tax Norwegian Administration and Statistics Norway. Jobs classified as ordinary and maritime in the A-Scheme register correspond to employees' population in the earlier Employee register. Still, the earlier Employee register was supposed to contain all job relations scheduled to more than four hours a week and lasting more than six days. Under the A-Scheme Act[26], the reporting duty for an employer occurs for all his employees with payroll or expenditure allowance above 1,000 Norwegian kroner per annum. Due to this new and more strict reporting duty, the new A-Scheme register has a wider scope than the earlier Employee register (Aa-register), which has produced a level shift and a break in the seasonal pattern.

Due to the transition to the A-Scheme register, the quality of the old Aa-register register declined towards the end. Due to the low quality in the old Aa-register for periods 2014M10, 2014M11 and 2014M12, the best version of the A-Scheme register for 2015M2 is used instead. [27] The A-Scheme register observation for 2015M1 is used, even though there were some start-up challenges in the new register, especially January 2015 even for late versions after many changes and replacement notifications were incorporated. These end and start-up problems – as well as change in level and seasonal pattern, and the fact that only version 1 of the A-Scheme register is available for the last observation – were modelled in the regARIMA-model in the seasonal adjustment software X-

[24] If an estimated variable = 0 in all waves one month for a group, 3-month centered average (3MA) of $\hat{p}_d$ is used instead for more robust standard error calculation. It has happened 5 times so far, all cases are for the unemployed aged 55-74 by sex, for men 2007M12 and 2008M9 and for women 2009M6, 2009M9 and 2014M5. If this should happen again, i.e. at the end of a time series, the average of the last 2 months is used instead (because a 3-month centered average is not available).
[25] See U.S. Census Bureau (2017).
[26] The employer's reporting of employment and income conditions Act, etc. (the a-opplysnings Act) § 3.
[27] The best version of the A-Scheme register for 2015M2 at the time of implementation of the new estimation procedure in the LFS was version 11 produced 2016.03.14, and that version is used here as well.

13ARIMA-SEATS. These breaks were specified as a sequence of additive outliers 2014M10-2015M1, a level shift for 2014M10, consequently using 11 seasonal outliers in 2015, and an additive outlier for the last observation 2021M10, respectively.[28]

The table below shows some results for the pre-adjustment regression models. A significant level-shift for all domains is seen for the change from the Aa-register to the A-Scheme register, as well as a change in the seasonal pattern. Also, we see a significant difference in level in the A-Scheme register between the first and later versions, which is not available for the last observation, in ongoing production, modelled as an additive outlier (AO2021.10).

Table 3.1 Parameter estimates, standard errors and T-values for the pre-adjustment variables for register employees by domain from X-13ARIMA-SEATS

	Female 15-24			Female 25-74			Male 15-24			Male 25-74		
Variable[1]	Estimate	Std. Err.	t-value	Estimate	Std. Err.	t-value	Estimate	Std. Err.	t-value	Estimate	Std. Err.	t-value
AO2014.10	-1 535	3 370	-0.46	-30 096	5 025	-5.99	-4 610	3 317	-1.39	-39 584	6 237	-6.35
LS2014.10	29 124	3 821	7.62	46 436	5 650	8.22	19 368	3 742	5.18	17 641	7 078	2.49
AO2014.11	-3 041	2 798	-1.09	-29 834	4 257	-7.01	-5 633	2 806	-2.01	-37 878	5 147	-7.36
AO2014.12	-5 214	2 174	-2.40	-26 580	3 343	-7.95	-6 852	2 201	-3.11	-34 396	3 742	-9.19
AO2015.1	-12 935	1 382	-9.36	-25 637	2 033	-12.61	-12 977	1 521	-8.53	-47 825	2 273	-21.04
SO2015.1	-2 151	1 379	-1.56	-10 379	911	-11.40	-5 415	1 368	-3.96	-18 313	1 022	-17.93
SO2015.2	-3 572	2 015	-1.77	-8 572	1 372	-6.25	-5 927	1 869	-3.17	-14 709	1 552	-9.47
SO2015.3	-4 288	2 319	-1.85	-7 884	1 628	-4.84	-5 272	2 135	-2.47	-12 246	1 958	-6.26
SO2015.4	-3 242	2 516	-1.29	-9 628	1 790	-5.38	-4 975	2 308	-2.16	-13 123	2 203	-5.96
SO2015.5	-1 078	2 636	-0.41	-8 517	1 883	-4.52	-1 183	2 412	-0.49	-11 385	2 341	-4.86
SO2015.6	560	2 694	0.21	-3 570	1 918	-1.86	-1 378	2 460	-0.56	-7 831	2 391	-3.28
SO2015.7	3 959	2 696	1.47	-4 563	1 897	-2.40	4 183	2 457	1.70	-9 107	2 359	-3.86
SO2015.8	5 533	2 642	2.09	-10 937	1 820	-6.01	6 803	2 401	2.83	-12 835	2 241	-5.73
SO2015.9	2 775	2 526	1.10	-8 248	1 678	-4.92	328	2 287	0.14	-10 520	2 021	-5.20
SO2015.10	-2 750	2 146	-1.28	-6 099	1 403	-4.35	-3 046	1 973	-1.54	-8 539	1 586	-5.38
SO2015.11	-3 887	1 446	-2.69	-6 083	921	-6.61	-3 432	1 418	-2.42	-7 280	1 030	-7.07
AO2021.10	13 327	1 469	9.07	9 642	2 053	4.70	11 334	1 596	7.10	12 344	2 292	5.39

[1] In the first column, the pre-adjustment variables for Additive Outliers, Level Shifts and Seasonal Outliers are abbreviated AO, LS and SO, respectively, followed by the date of the intervention.
Source: Statistics Norway.

Register unemployed (layoff-harmonized)

Due to different treatment of temporary layoffs, there is a large break in the observed relationship between LFS-unemployed and the official figures of registered unemployed at the Norwegian Labour and Welfare Administration (NAV) the first couple of months of the COVID19-pandemic in Norway starting in March 2020.[29] Therefore, "layoff-harmonized" figures of register unemployed for each month in 2020 and 2021 are constructed by excluding temporary layoffs the first 3 months from the official figures from NAV.[30] This harmonization makes the definition more in line with the definition of unemployment in the LFS, because LFS treats them as employed temporarily absent for

[28] The X-13ARIMA-SEATS-specifications include no log-transformation of data, and the old (conservative) automatic model selection procedure pickmdl{} in order for the ARIMA-structures to change little. The first OK model is selected among 5 prespecified. For more information about the pickmdl{} procedure, please see the X-13ARIMA-SEATS Reference Manual or Dagum (1988). The chosen ARIMA-structures for the 4 domains are:
Male 15-24: ARIMA=(0 1 1)(0 1 1)
Male 25-74: ARIMA=(0 1 2)(0 1 1)
Female 15-24: ARIMA=(0 1 1)(0 1 1)
Female 25-74: ARIMA=(0 1 1)(0 1 1)

[29] Due to extraordinary situation from March 2020 without historical comparison in the number of applications for unemployment benefits from laid offs and ordinary unemployed, there were some delays case processing time. For our layoff-harmonized time series only negligible quality issues are expected.
[30] We started with this limitation in 2020 partly due to missing data and partly because the number of layoffs before 2020 was more negligible.

the first 90 days. This harmonization of the register variables is done to get a more stable and higher correlation between the register and the LFS variable.[31]

Two-months moving average of the stock of pre-adjusted harmonized register unemployed
The official figures from NAV for unemployed persons are the number of registered unemployed close to the end of the month. For our auxiliary register variable to be more representative of the monthly average of unemployed according to LFS, we use the average of the auxiliary register variable close to the end of the month and the end of the previous month. This averaging of our pre-adjusted harmonized register unemployment variable is important in months with large changes of unemployment, such as for the COVID-19 pandemic shut-down in Norway in March 2020.

[31] This register variable is pre-adjusted in X-13ARIMA-SEATS as well, for two minor effects compared to the huge changes in 2020: a) reminder by SMS from July 2018 to the unemployed to send report cards modeled as a level shift (LS2018.7), b) a new registration system at NAV in November 2018 for all who register as jobseekers which get jobseekers faster into the statistics of registered jobseekers, modeled as a gradual (square decreasing) break from and including November 2018 to January 2019 (predefined variables QD2018.10-2019.1 in the software), which seems to best mimic the development of the effects, also reported by NAV.

4. Results

In this section, we present estimated hyperparameters and other model results, as well as the final break estimates due to the 2021 LFS-redesign.

4.1. Estimated hyperparameters and other results

Table 4.1(a) and 4.1(b) provides an overview of the maximum likelihood estimates of the hyperparameters from the R-package KFAS. The tables also include the estimated COVID-19 inflation parameter Ψ_A and Ψ_B based on grid search for rescaling of hyperparameters related to the trend in different periods and estimated autocorrelation in the survey errors, Φ. In many of the figures in Appendices B and C, we use the notation $K1 = \Psi_A$ and $K2 = \Psi_B$.

Table 4.1(a) Selected estimated hyperparameters for employed persons and break adjusted register employees from the smooth trend model based on data for 2006M1-2021M10

	Male 15-24	Male 25-74	Female 15-24	Female 25-74
Employed persons (LFS):				
$\Psi_A = K1$	25	16	25	49
$\Psi_B = K2$	13	2.875	13	13
$\sigma^2_{R,LFS}$	17283.5	291202.1	22823.9	33320.3
σ^2_{ω}	15224.7	12693.7	5548.9	10.8
σ^2_{I}	1218093.3	375.0	4531639.3	1380485.5
σ^2_{λ}	1.0	2.8	9.3	42.1
$\sigma^2_{e_1}$	11502.4	11805.6	10584.6	13139.7
$\sigma^2_{e_2} = \sigma^2_{e_3} = \ldots = \sigma^2_{e_8}$	7131.1	5384.5	6936.6	4545.6
Break-adjusted register employees:				
$\sigma^2_{\mathrm{R,REG.}}$	23271.6	453089.5	36013.0	47471.1
σ^2_{ω}	5531.5	0.0	4465.4	2958.4
σ^2_{I}	210973.8	730098.7	61690.2	364957.9
$Cov(w_t^{R,LFS}, w_t^{R,X}) = \sigma^2_{R,LFS\_X}$	20055.3	363008.1	28669.8	39771.3
$\mathrm{Corr}(w_t^{R,LFS}, w_t^{R,X})$	1.0000	0.9994	1.0000	1.0000
Max. log. likelihood value	-11011.0	-11744.5	-10946.8	-11677.3
Φ	0.577	0.723	0.539	0.770

Note: $Corr(w_t^{R,LFS}, w_t^{R,X}) = \sigma^2_{R,LFS_X} / \sqrt{\sigma^2_{R,LFS}\, \sigma^2_{R,\mathrm{REG}}}$

Source: Statistics Norway.

In tables 4.1(a) and 4.1(b), we see that the optimal value the inflation parameter Ψ_A for rescaling of hyperparameters related to the trend in the first half of 2020 is a lot higher than Ψ_B for the later "recovering" period of COVID-19 pandemic. This was expected, because the first initial shut-down part of the coronavirus pandemic had the larget fluctuations in labour market figures.

For all the groups in tables 4.1(a) and 4.1(b), we see that the estimated correlation for the error term of the slope of the trend between LFS and register is equal or almost equal to 1. This quite strong correlation is an advantage for the joint modeling of LFS and register variable and the estimation of possible break due to the 2021 LFS-redesign.

Due to normally more stable labour market status over time for persons aged 25-74 than for persons aged 15-24, we see in Tables 4.1(a) and 4.1(b) that the estimated autocorrelation in the survey errors, Φ, is higher for groups with persons aged 25-74 than for persons aged 15-24. Due to unemployment according to LFS has a tendency to be a less stable labour market status over time, we also see that the estimated autocorrelation in the survey errors, Φ, is a lot lower in table 4.1(b) than in table 4.1(a) for employment.

Table 4.1(b) Selected estimated hyperparameters for unemployed persons and 2-moth moving average of break adjusted lay-off harmonized register unemployed from the smooth trend model based on data for 2006M1-2021M10

Hyperparameter	Male 15-24	Male 25-74	Female 15-24	Female 25-74
Unemployed persons (LFS):				
$\Psi_A = K1$	16	16	49	25
$\Psi_B = K2$	1.3125	2.25	5	4
$\sigma^2_{R,LFS}$	4455.7	105434.3	1088.9	35787.3
σ^2_{ω}	1058.7	58.9	1251.7	6053.0
σ^2_I	232.6	1.3	2379962.9	494.1
σ^2_{λ}	0.0	14.7	0.1	6.0
$\sigma^2_{e_1}$	12240.9	15792.6	13085.8	18299.5
$\sigma^2_{e_2} = \sigma^2_{e_3} = \ldots = \sigma^2_{e_8}$	11477.6	13461.7	11423.3	11180.1
2-months moving average of break adjusted lay-off harmonized register unemployed:				
$\sigma^2_{\mathrm{R,REG.}}$	6826.8	158445.5	*1534.2*	46489.5
σ^2_{ω}	3.5	0.0	0.0	5.7
σ^2_I	0.0	0.1	0.0	1.5
$Cov(w_t^{R,LFS}, w_t^{R,X}) = \sigma^2_{R,LFS\_X}$	5463.3	129229.4	1291.6	40788.9
$\mathrm{Corr}(w_t^{R,LFS}, w_t^{R,X})$	0.9906	0.9998	0.9993	1.0000
Max. log. likelihood value	-9833.4	-10665.0	-9640.0	-10263.8
ϕ	0.106	0.259	0.081	0.267

Note: $Corr(w_t^{R,LFS}, w_t^{R,X}) = \sigma^2_{R,LFS\_X} / \sqrt{\sigma^2_{R,LFS}\,\sigma^2_{R,\mathrm{REG}}}$

Source: Statistics Norway.

4.2. Level shift parameter estimates and standard error for the 2021 LFS-redesign

Table 4.2 Final average smoothed 2021-redesign level shift parameter estimates and corresponding conditional standard error for employed persons and on unemployed persons according to the Norwegian LFS, by gender and age, based on data ending at 2021M10

	Employed persons		Unemployed persons	
Gender and age	Parameter estimate	Standard error	Parameter estimate	Standard error
Total indirect by 4 domains (gender : 2 age grp.)	21 864	6 295	5 371	3 659
Male and Female aged 15-24 (indirect by gender)	6 507	3 110	8 215	2 206
Male and Female aged 25-74 (indirect by gender)	15 357	5 473	-2 844	2 918
Male (indirect by age, more / less than 24)	-1 989	4 612	1 723	2 880
Female (indirect by age, more / less than 24)	23 853	4 285	3 648	2 257
Female aged 15-24	8 115	2 145	4 940	1 442
Female aged 25-74	15 738	3 709	-1 292	1 736
Male aged 15-24	-1 608	2 252	3 275	1 670
Male aged 25-74	-381	4 025	-1 552	2 346

Source: Statistics Norway.

The estimated uncertainties for the 2021-redesign level shift parameter estimates measured with the standard error reported in the table 4.2 is based on the case that K1 and K2 are known. If we take into account that K1 and K2 are unknown, the uncertainty for the level shift parameter estimates becomes greater. Similarly, prior estimates of the autoregressive parameters for the sampling error component also point in the direction that the uncertainty of the 2021-redesign level shift parameter is underestimated, but the contribution from this is probably less than compared with the effect of K1 and K2. Also, the covariance of the estimated level shift parameter between different waves should ideally be included. Here, we have not taken that into account, and only added the estimated variance for the estimated level shift parameter for the waves.

For women aged 15-24 years, we find a positive and significant break estimate for both the series for the number of employed and the number of unemployed people. The estimates correspond to about 8,000 and 5,000 persons, respectively. For women aged 25-74 years, we only find a significant effect for the number of employed individuals, which corresponds to about 16,000 persons. The corresponding insignificant estimate for the number of unemployed individuals for this age group is about -1,300 individuals. Strictly speaking, only one of the estimates related to men is significant. The estimate for unemployed men aged 15-24 is just significant at the 5 percent level. The estimate is about 3,300 persons. In contrast, the estimate for the agegroup 25-74 years, is negative. In conjunction with the number of employed men, one has found a small and negative estimate for both age groups.

For the total, indirectly modeled through the 4 domains, we find a positive and significant break estimate of about 22,000 employed persons. The total break estimate for unemployed persons is around 5,000, but the change is not significant at the 5 percent significance level.

Table 4.3 Final smoothed 2021-redesign level shift parameter estimates and standard error (Std. err.) for employed and unemployed persons, by gender, age and wave, based on data ending at 2021M10

		Male				Female			
		Employed persons		Unemployed Persons		Employed persons		Unemployed persons	
Age and wave		**Estimate**	**Std. err.**	**Estimate**	**Std. err.**	**Estimate**	**Std. err.**	**Estimate**	**Std. err.**
15-24	1	**630**	6 189	**3 027**	4 177	**19 914**	5 779	**7 412**	3 611
	2	**13 227**	6 050	**238**	4 589	**10 912**	5 819	**-1 342**	3 962
	3	**928**	6 145	**9 819**	4 716	**7 063**	5 845	**6 364**	4 046
	4	**-3 293**	6 417	**195**	4 793	**8 420**	6 104	**1 267**	4 168
	5	**-6 381**	6 337	**4 599**	4 801	**2 624**	6 194	**7 844**	4 204
	6	**-10 378**	6 481	**5 248**	4 876	**2 387**	6 256	**3 907**	4 173
	7	**148**	6 516	**689**	4 901	**2 350**	5 998	**8 217**	4 138
	8	**-7 745**	6 791	**2 385**	4 898	**11 251**	6 510	**5 847**	4 298
	Average	**-1 608**	**2 252**	**3 275**	**1 670**	**8 115**	**2 145**	**4 940**	**1 442**
25-74	1	**-13 846**	12 560	**3 560**	6 820	**10 314**	11 570	**-2 915**	5 733
	2	**-7 963**	11 754	**-3 327**	6 893	**18 648**	10 481	**1 564**	4 980
	3	**-7 691**	11 195	**-4 527**	6 711	**18 179**	10 846	**3 576**	4 852
	4	**1 005**	10 404	**-6 359**	6 540	**13 331**	10 396	**-1 746**	4 692
	5	**-2 716**	10 943	**-4 878**	6 492	**12 803**	10 050	**2 077**	4 663
	6	**7 821**	11 453	**5 650**	6 540	**9 761**	10 178	**-6 364**	4 728
	7	**11 994**	10 811	**-3 375**	6 540	**28 813**	9 981	**754**	4 770
	8	**8 351**	11 809	**842**	6 542	**14 051**	10 333	**-7 283**	4 764
	Average	**-381**	**4 025**	**-1 552**	**2 346**	**15 738**	**3 709**	**-1 292**	**1 736**

Source: Statistics Norway.

5. Sub-group break estimate distribution and back calculated break adjusted series

This section describes how sub-group break estimates are made and how the back-calculated break adjusted time series are made.

Let b_i be the average of 8 waves of the estimated 2021 redesign level shift parameters for employed or unemployed persons in group *i* described in previous chapters.

Now we define a level shift variable, LS2021M1, where <u>LS2021M1 is defined as **-1** for the period 2006M1 to 2020M12</u> and the value zero for 2021M1 and onwards, to break-adjust figures before the 2021 redesign easily.

$b_i/P_i^{2020M12}$ is the relative break parameter for employed/unemployed persons, where $P_i^{2020M12}$ is the number of persons in population group i at 2020M12.

Let Y_i^t be the estimated number of employed or unemployed persons in group *i* at time t based on LFS.

The relative break adjusted LFS figures for the number of employed or unemployed persons consistent with post 2021-redesign level is then (using Y_i^t and b_i for the same LFS-variable)

(18) Y_i^t - LS2021M1* $(b_i/P_i^{2020M12})\ P_i^t = Y_i^t$ – LS2021M1 *$b_i\,(P_i^t/P_i^{2020M12})$.

For the period before the 2021 redesign, due to the definition of LS2021M1, being -1 before the redesign, the back-casted relative break adjusted LFS figure is then:

(19) $Y_i^t + b_i\,(P_i^t/P_i^{2020M12})$,

where *i* is limited to the following 4 groups in the separate modelling of employed and unemployed persons, due to relatively small monthly wave-divided sample sizes: gender cross-classified by the following the two age groups 15-24 and 25-74.

Construction of more detailed subgroup estimates

According to the EU-regulation, more detailed back-calculated break-free time series for the main LFS are required for the quarterly LFS.[32] Even more detailed sub-group estimates are optional. For more detailed sub-group break estimates, we need to split the results for persons aged 15-24 into results for persons aged 15-19 and 20-24, and the results for persons aged 25-74 need to be split into results for the 3 age groups 25-54, 55-64 and 65-74**,** all cross-classified by gender.

5.1. Time-varying splitting factor based on the monthly LFS

The time varying splitting factors for the young are:[33]

(20) $\mathbf{f^t_{20\text{-}24} = (Y^t_{20\text{-}24} / Y^t_{15\text{-}24})}$ and $\mathbf{f^t_{15\text{-}19} = (Y^t_{15\text{-}19} / Y^t_{15\text{-}24})}$,

which means that f^t_i are between 0 and 1 and that $(f^t_{15\text{-}19} + f^t_{20\text{-}24}) = 1$. Correspondingly

(21) $\mathbf{f^t_{25\text{-}54} = Y^t_{25\text{-}54} / Y^t_{25\text{-}74}}$, $\mathbf{f^t_{55\text{-}64} = Y^t_{55\text{-}64} / Y^t_{25\text{-}74}}$ and $\mathbf{f^t_{65\text{-}74} = Y^t_{65\text{-}74} / Y^t_{25\text{-}74}}$,

[32] Article 10 of COMMISSION IMPLEMENTING REGULATION (EU) 2019/2240.

[33] Here the specification of gender is omitted for the ease of exposition. Note also that there are separate splitting factors for the variable, Y, for employed persons and for unemployed persons.

which means that f^t_i are between 0 and 1 and ($f^t_{25\text{-}54} + f^t_{55\text{-}64} + f^t_{65\text{-}74}$) = 1.

We have decided to use a monthly time-varying splitting factor based on LFS. Due to a relatively small sample, the factors will be volatile over time, especially for rare events in small groups, such as unemployed male/female 65-74. From time to time, we will then get $f^t_{65\text{-}74} = 0$. However, this happens when nobody in our monthly net sample aged 65-74 are unemployed in a particular month. In that case, we allocate the break estimate to the other sub-groups within the age group 25-74, so we are guaranteed not to get negative break adjusted figures in the case of negative break estimates.

5.2. Calculation of relative break adjusted sub-groups figures before 2021

The time-varying splitting factors are then used to produce relative break estimates for the sub-groups (B^t_i) assuming proportionality, for example:

(22) $$B^t_{20\text{-}24} = b_{15\text{-}24}\ (P^t_{\mathbf{15}\text{-}24}/P^{2020M12}_{\mathbf{15}\text{-}24})\ f^t_{20\text{-}24}\ .$$

We then get back-calculated relative break adjusted LFS estimates for the sub-groups, which can be rearranged to get a time varying multiplicative factor(MF):

(23) $$Y^t_{20\text{-}24} + b_{15\text{-}24}\ (P^t_{15\text{-}24}/P^{2020M12}_{15\text{-}24})\ f^t_{20\text{-}24} =$$

$$Y^t_{20\text{-}24} + b_{15\text{-}24}(P^t_{15\text{-}24}/P^{2020M12}_{15\text{-}24})\ (Y^t_{20\text{-}24} / Y^t_{15\text{-}24}) =$$

$$Y^t_{20\text{-}24} + Y^t_{20\text{-}24}(b_{15\text{-}24} / Y^t_{15\text{-}24})\ (P^t_{15\text{-}24}/P^{2020M12}_{15\text{-}24}) =$$

$$Y^t_{20\text{-}24} * [1 + (b_{15\text{-}24} / Y^t_{15\text{-}24})\ (P^t_{15\text{-}24}/P^{2020M12}_{15\text{-}24})] =$$

$$Y^t_{20\text{-}24} * [1 + (b_{15\text{-}24} /P^{2020M12}_{15\text{-}24}) * (P^t_{15\text{-}24} /Y^t_{15\text{-}24})] =$$

$$Y^t_{20\text{-}24} * [1 + (b_{15\text{-}24} /P^{2020M12}_{15\text{-}24}) / (Y^t_{15\text{-}24} / P^t_{15\text{-}24})] = Y^t_{20\text{-}24} * MF^t_{20\text{-}24}\ .$$

The multiplicative factor (MF) consists of a time-varying part in the denominator of the second term ($Y^t_{\mathbf{15\text{-}24}}$ **/** $P^t_{\mathbf{15\text{-}24}}$), which is the estimated LFS proportion at time *t* for the main domain (15-24). It also consists of a constant part in the numerator of the second term ($b_{\mathbf{15\text{-}24}} /P^{2020M12}_{\mathbf{15\text{-}24}}$**),** which is the estimated break parameter for the main domain (15-24) relative to the population in the main domain in December 2020. A corresponding method is used for other sub-groups.

This kind of relative break adjustment for subgroups will ensure that the sum of subdomain break estimates always will be equal to the main domain break estimates, for example:

(24) $$B^t_{15\text{-}19} + B^t_{20\text{-}24} =$$

$$b_{15\text{-}24}\ f^t_{15\text{-}19}\ (P^t_{\mathbf{15}\text{-}24}/P^{2020M12}_{\mathbf{15}\text{-}24}) + b_{15\text{-}24}\ f^t_{20\text{-}24}\ (P^t_{\mathbf{15}\text{-}24}/P^{2020M12}_{\mathbf{15}\text{-}24}) =$$

$$b_{15\text{-}24}(f^t_{15\text{-}19} + f^t_{20\text{-}24})\ (P^t_{\mathbf{15}\text{-}24}/P^{2020M12}_{\mathbf{15}\text{-}24}) =$$

$$b_{15\text{-}24}(P^t_{\mathbf{15}\text{-}24}/P^{2020M12}_{\mathbf{15}\text{-}24}) = b_{15\text{-}24}\ (P^t_{\mathbf{15}\text{-}24}/P^{2020M12}_{\mathbf{15}\text{-}24}) = B^t_{15\text{-}24}.$$

Given the assumption of proportionally distributed breaks, the time-varying multiplicative factors (MF^t_{domain}) are merged onto all the LFS-microdata before 2021. We use one set of multiplicative factors for employed persons and one for unemployed persons. Then the factors can easily be used to make many different detailed break adjusted estimates before 2021 for the main indicators.

Based on all these LFS-microdata with monthly adjustment factors, we also apply them with quarterly frequency. Then we are using our week-proportional quarterly weighting factor[34] to produce back-calculated quarterly estimates adjusted for the break due to the 2021 LFS-redesign for main indicators for different required and optional breakdowns. These back-calculated quarterly estimates were reported to Eurostat using the proper EDAMIS channel and template for the transmission.[35]

However, the validity of the assumption is difficult to assess. This uncertainty regarding the validity of the assumption about proportionally distributed breaks builds on top of the uncertainty of the break estimates of the main domains, so one should be careful about making too detailed subdomain break estimates.

[34] The week-proportional quarterly weighting factor are the monthly mmc-weights multiplied by 4/13 or 5/13 depending on whether the months in the LFS contain respectively 4 or 5 whole weeks. For more information see Oguz-Alper (2018).
[35] EDAMIS Web Portal enables transmissions of data to the Eurostat Single Entry Point. The final break estimates was transmitted to Eurostat on December 21st 2021.

6. Adjustment of the time series model for the production of LFS-trend estimates

Despite utilizing many (strong) auxiliary register variables in the weighting procedure in the Norwegian LFS, the relatively small monthly LFS-sample gives too volatile seasonally adjusted monthly unemployment figures that we usually do not publish; see Figure 6.1. Therefore, Statistics Norway publishes 3-month moving centred averages (3MMA) of the seasonally adjusted figures. Unfortunately, this procedure “loses” the last observation when the figures are named by the middle month of the average, and is not in line with the new MUR-regulation.[36] Forecasting the seasonally adjusted monthly figures one extra time period before taking the 3MMA may be a solution, but would give additional uncertainty in the end.

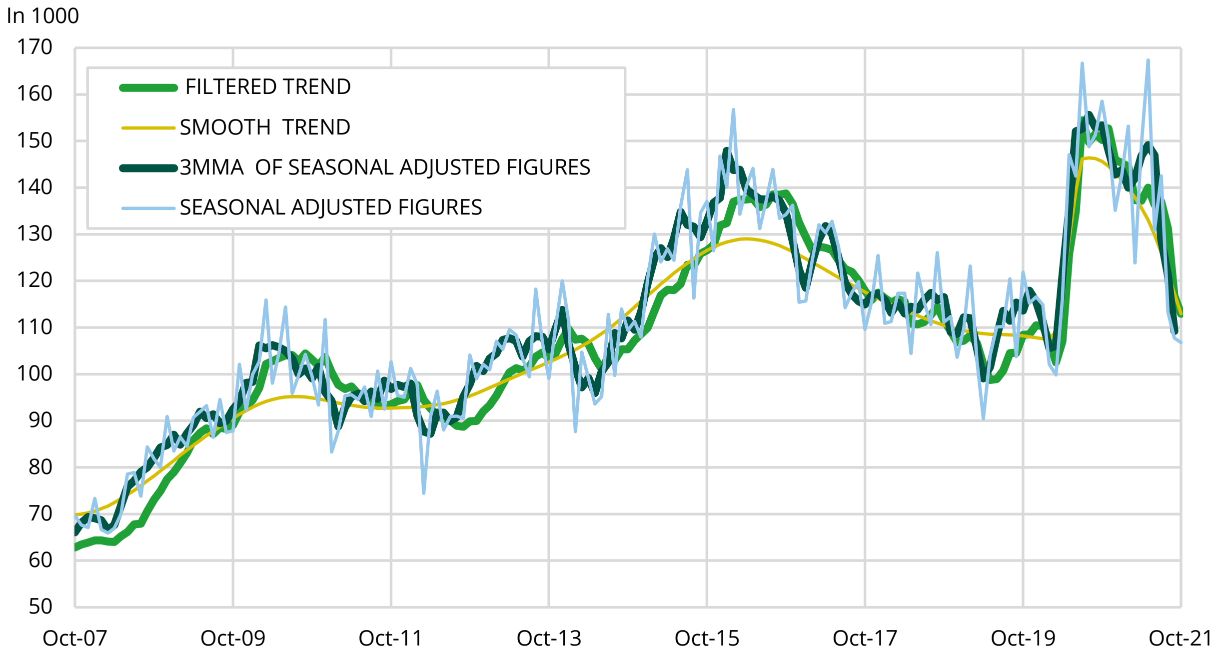
State space models can improve the precision of the monthly estimates by utilizing sample information from previous periods and can give filtered or smoothed revised LFS-trends, also for the last observed month. However, Norwegian users are less familiar with these types of trend figures than the more traditional (filter-based) seasonally adjusted figures (X-12-ARIMA).

To make monthly LFS figures, we adjust the state space models to produce pure LFS-trends that are not directly affected by the register time series. The adjusted model does not include auxiliary register time series. We have used a new grid search to obtain optimal values for the COVID-19 inflation parameters for rescaling hyperparameters related to the trend described in Section 2.3. The adjusted model does not estimate the 2021-redesign level shift parameter but instead takes as input the final average estimates from the state space models described in Sections 2 and 4.

Figures 6.1 and 6.2 compare filtered and smoothed trends from these models with similar results based on (filter-based) seasonal adjustment (X-13ARIMA-SEATS) of monthly time series break adjusted before 2021 with the same final average estimated 2021-redesign level shift parameters, with and without 3MMA in the aftermath.

[36] Commission Implementing Regulation (EU) 2019/2241

Figure 6.1 The number of unemployed persons aged 15-74, adjusted for 2021-redesign before 2021 indirectly by aggregating over groups. Seasonally adjusted in X-12-ARIMA without and with 3-month moving average (3MMA) afterwards and filtered and smoothed trend from the adjusted time series model. In 1000[1]



[1] Due to the extreme volatility of the filtered trend in the first initial periods, the presented time series here starts in October 2007.
Source: Statistics Norway.

Figure 6.1 shows that the filtered trend from the adjusted time series model is quite similar to the seasonally adjusted[37] figures smoothed with a 3-month moving average (3MMA). This is the case both in the first decade and towards the end with the extreme changes due to the COVID-19 pandemic. We interpret this similarity across 2020 and 2021 as a sign that our way of increasing the flexibility of the smooth trend model is quite reasonable.

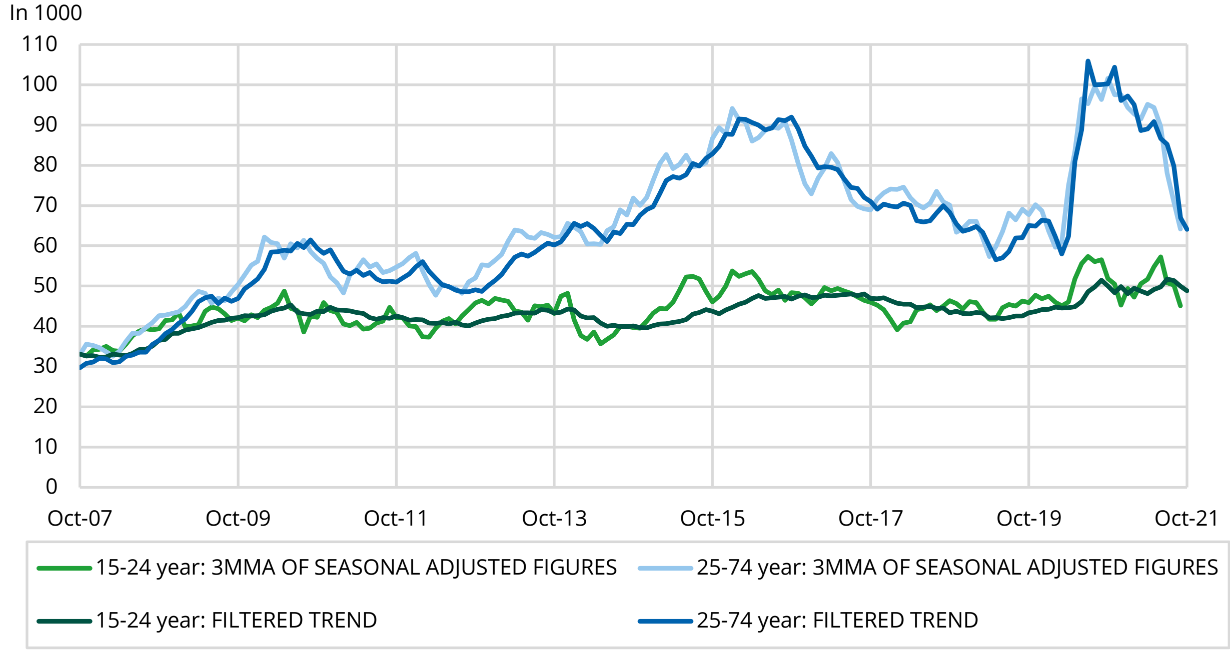
The similarity of the filtered trend and the 3MMA of seasonally adjusted figures in the first decade indicates that the *absolute* break adjustment in the additive smooth trend model and the *relative* break adjustment used for pre-correcting the monthly time series before the seasonal adjustment do not seem to make a noticeable difference.

The smoothed trend from the adjusted time series model is quite smooth and does not follow the 3MMA of the seasonally adjusted that well.

For the production of monthly unemployment from state space models, the filtered trend would be a natural choice.[38] It is more similar to the 3MMA of the seasonally adjusted figures and will give minor revisions than the smoothed trend. According to the MUR-regulation, minor revisions are one of the quality aspects that shall be monitored for the overall monthly unemployment rate every three years. However, volatility is the other quality aspect, where a smooth trend would be preferable. [39]

[37] We have used the recommended practice for handling COVID-19 pandemic in seasonal adjustment made by Division for methods at Statistics Norway, see https://github.com/statisticsnorway/SeasonalAdjustmentCorona
[38] For MUR, the filtered trend estimates are recommended in studies form the Netherlands and United Kingdom, see Brakel and Krieg (2015) and Elliott and Zong (2019), respectively.
[39] See annex IV of the Commission Implementing Regulation (EU) 2019/2241

Figure 6.2 The number of unemployed persons by age. Filtered trend and 3MMA of seasonally adjusted figures[1]

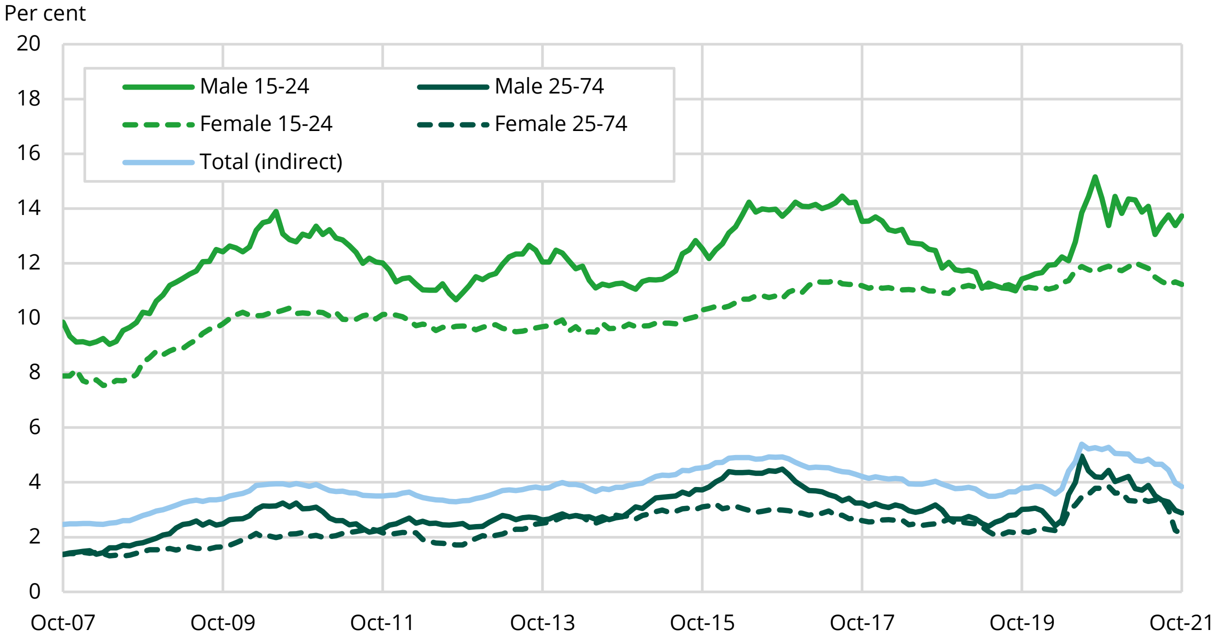


[1] Figures before 2021 are adjusted for the 2021 LFS-redesign. Due to the extreme volatility of the filtered trend in the first initial period, the presented time series here starts in October 2007.
Source: Statistics Norway.

Time series derived from rotating panel surveys such as our LFS include sample errors that are correlated over time. Standard seasonal adjustment procedures such as X-12-ARIMA do not account for this, and spurious trends may be the consequence. This was first pointed out by Hausman and Watson (1985). Especially for subgroups based on small samples with large sampling errors, spurious trends may be a problem, as pointed out in Pfeffermann, Feder and Singnorelli (1998). In our state space model, the correlated survey errors are modelled.[40] The larger deviation of the 3MMA of the seasonally adjusted figures from the filtered trend for unemployed persons aged 15-24 seen in Figure 6.2 from time to time may be a sign of such a spurious trend.

[40] As alternative time series to filtered trends from state-space models, monthly figures corrected for both systematic seasonal variation and systematic (auto)correlated sampling errors (due to the rotation pattern) may be more in line with the MUR-regulation. Autocorrelated sampling errors may be systematic effects that do not have to do with the development in the actual labour market, and not taking this into account makes the figures more volatile than necessary. Such figures may be derived directly from a state-space model or indirectly by preadjusting the time series for (auto)correlated sampling errors and then carrying out seasonal adjustment in X12-ARIMA as in Mayer (2018).

Figure 6.3 Unemployed persons in per cent of the labour force (MUR) by month, gender and age. Filtered trend from the adjusted time series model[1]



[1] Figures before 2021 are adjusted for the 2021 LFS-redesign. Due to the extreme volatility of the filtered trend in the first initial periods, the presented time series here starts in October 2007.
Source: Statistics Norway

Figure 6.3 shows the filtered trend for the monthly unemployment rate for the 4 groups requested in the MUR-regulation, as well as the indirect total. For all the graphs, figures before 2021 are adjusted for 2021 LFS-redesign.

Due to the Omicron variant of the coronavirus (COVID-19) and the second period of national strict COVID-19 measures starting in December 2021, the situation did not go back to normal in late autumn 2021. Therefore, we must look further into how the trend model can be adjusted to adapt to future developments, before such models can be set in production.

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Appendix A: Accounting for survey errors

Because of the survey design, which implies that the respondents are asked questions 8 times over 2 years, that is each quarter over two years, the derived time series will be subject to autocorrelation. Neglecting the survey error component will bring about bias when it comes to other components. To simplify the numerical calculations, we pre-estimate the autocorrelation parameters related to the survey errors. Thus, the estimates of these parameters are plugged in when estimating the remaining parameters.

Construction of pseudo errors

Let E_t^i and U_t^i denote, respectively, the total number of employed and unemployed according to wave *i* (*i* =1,...,8) in period *t*. Let the time-specific means over the waves be given as $\bar{E}_t = \frac{1}{8}\sum_{i=1} E_t^i$ and $\bar{U}_t = \frac{1}{8}\sum_{i=1}^{8} U_t^i$. Furthermore, let the time index vary from 1 to *T*. The wave-specific means are then given by, respectively, $\bar{E}_i = \frac{1}{T}\sum_{t=1}^{T} E_t^i$ and $\bar{U}_i = \frac{1}{T}\sum_{t=1}^{T} U_t^i$, where *i*=1,...,8. The pseudo errors are now calculated by

(A.1) $$\varepsilon_{u,t}^i = U_t^i - \bar{U}_t - \bar{U}_i; i = 1,...,8; t = 1,...,T$$

and

(A.2) $$\varepsilon_{e,t}^i = E_t^i - \bar{E}_t - \bar{E}_i;\ i = 1,...,8; t = 1,...,T.$$

Model specification

For each domain, we estimate, separately, the following sets of regression models.

(A.3) $$\varepsilon_{u,t}^j = \phi_u \varepsilon_{u,t-3}^{j-1} + \xi_{u,t}^j,\ j = 2,...,8$$

(A.4) $$\varepsilon_{e,t}^j = \phi_e \varepsilon_{u,t-3}^{j-1} + \xi_{e,t}^j,\ j = 2,...,8$$

Each of the two systems is characterized by only one parameter in the systematic part, that is (the autocorrelation parameters) ϕ_u and ϕ_e, respectively. $\xi_{u,t}^j$ and $\xi_{e,t}^j$, where *j*=2,...,8, are error terms. Let us define the following vectors with errors.

(A.5) $$\xi_{u,t} = \left[\xi_{u,t}^2,\quad \xi_{u,t}^3,\quad \xi_{u,t}^4,\quad \xi_{u,t}^5,\quad \xi_{u,t}^6,\quad \xi_{u,t}^7,\quad \xi_{u,t}^8\right]'$$

and

(A.6) $$\xi_{e,t} = \left[\xi_{e,t}^2,\quad \xi_{e,t}^3,\quad \xi_{e,t}^4,\quad \xi_{e,t}^5,\quad \xi_{e,t}^6,\quad \xi_{e,t}^7,\quad \xi_{e,t}^8\right]'.$$

We assume that

(A.7) $\xi_{u,t} \sim NIID(0, \Omega_u)\forall t,$

and

(A.8) $\xi_{e,t} \sim NIID(0, \Omega_e)\forall t,$

where both Ω_u and Ω_e are full covariance matrices. The two models are estimated by the SURE procedure in the r-package Systemfit[41], see Henningsen and Hamann (2007). In Table A.1, we report the estimates of the autocorrelation parameters.

Table A.1 Estimates of the autocorrelation parameters (ϕ)

	Employment		Unemployment	
Domain	Estimate	Std. err.	Estimate	Std. err.
Females 15-24	0.539	0.023	0.081	0.027
Females 25-74	0.770	0.017	0.267	0.025
Males 15-24	0.577	0.022	0.106	0.027
Males 25-74	0.723	0.019	0.259	0.027

Source: Statistics Norway.

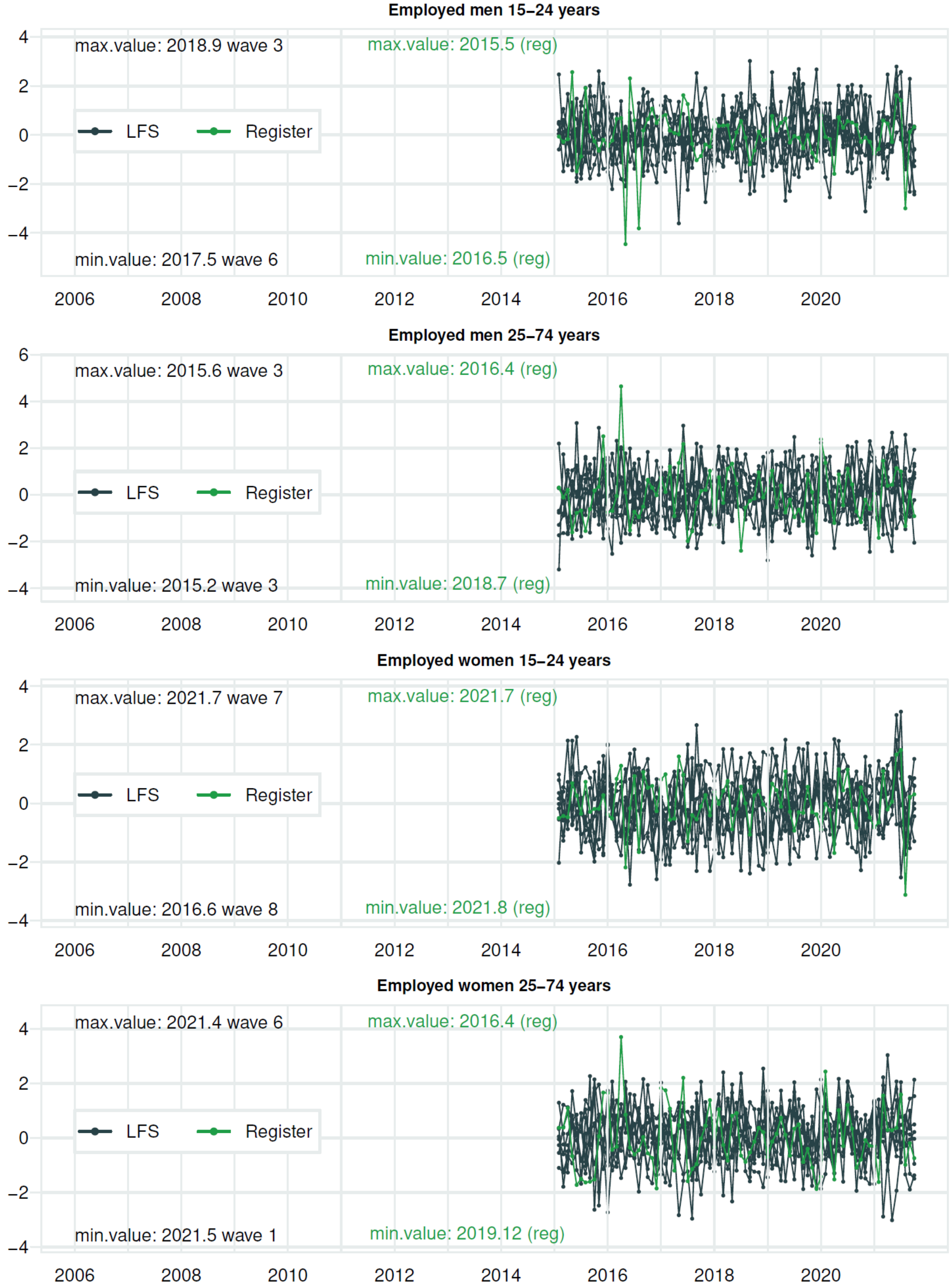
Issues of robustness

In modelling, we have put emphasis on employing a parsimonious model. The approach can be extended in different directions. One extension is to operate with wave-specific autocorrelation parameters. Unreported results show that the above implicit homogeneity assumptions are rather innocent. Another extension is to extend the lag-length, for instance by adding variables at the sixth lag. It is not entirely clear which lag-length to apply, so we have settled for the most parsimonious specification with respect to lag-length. We have also looked at specifications in which we model the pseudo-errors for employed and unemployed simultaneously. Under this more general model, we can for instance have that $\varepsilon_{u,t-3}^{j-1}$ influences $\varepsilon_{e,t-3}^{j}$. However, even if it is easy to estimate such a model in Systemfit, it turned out to be more difficult to handle this extension in the overall model. Finally, we also looked at more parsimonious specifications of the covariance matrices Ω_u and Ω_e, but the results seemed rather robust with respect to this type of change of the specification.

[41] https://CRAN.R-project.org/package=systemfit

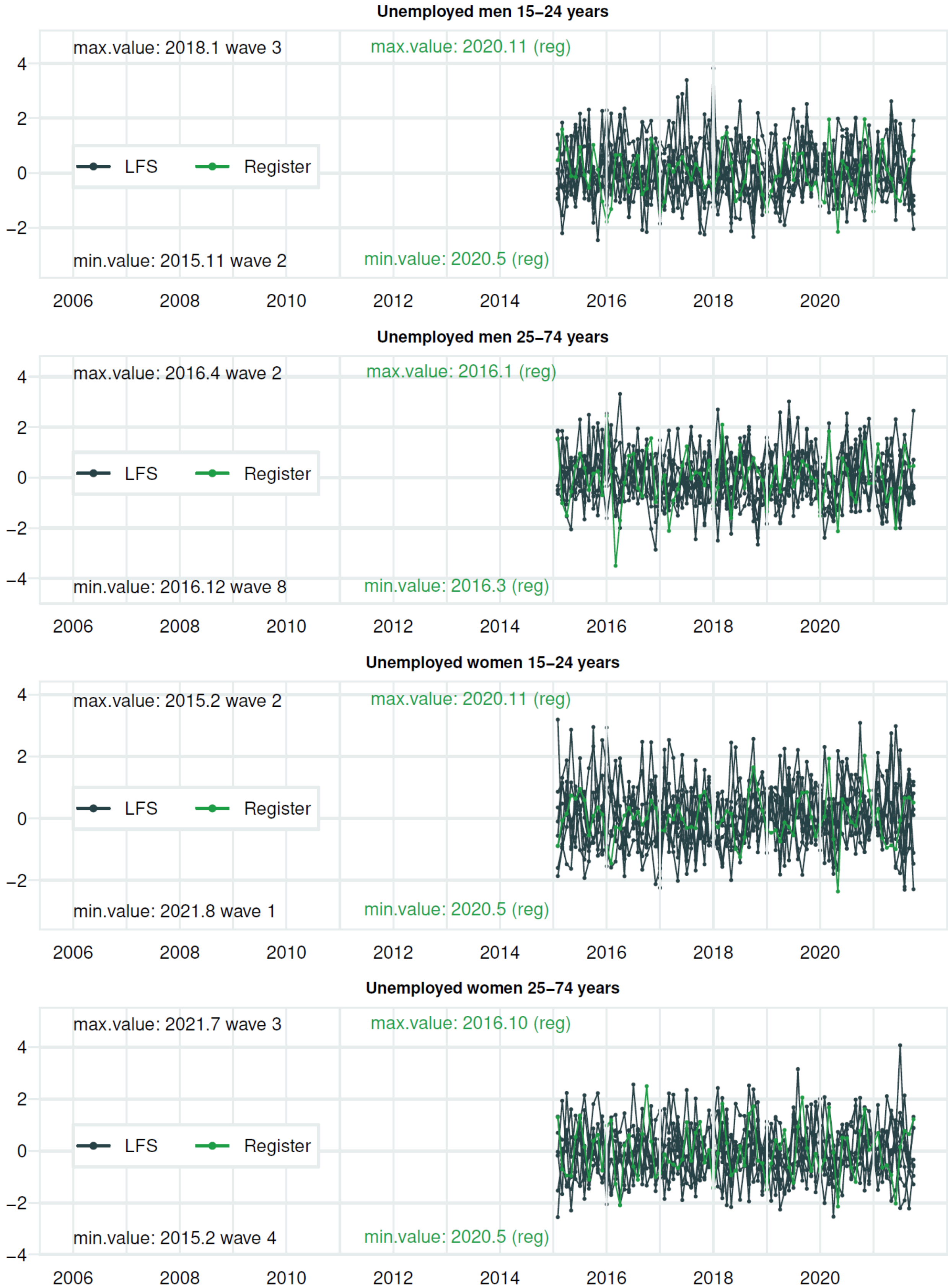
Appendix B: Model diagnostics

Figure B.1 Standardized recursive residuals for employed persons for the different LFS-waves and the register variable by sex and age



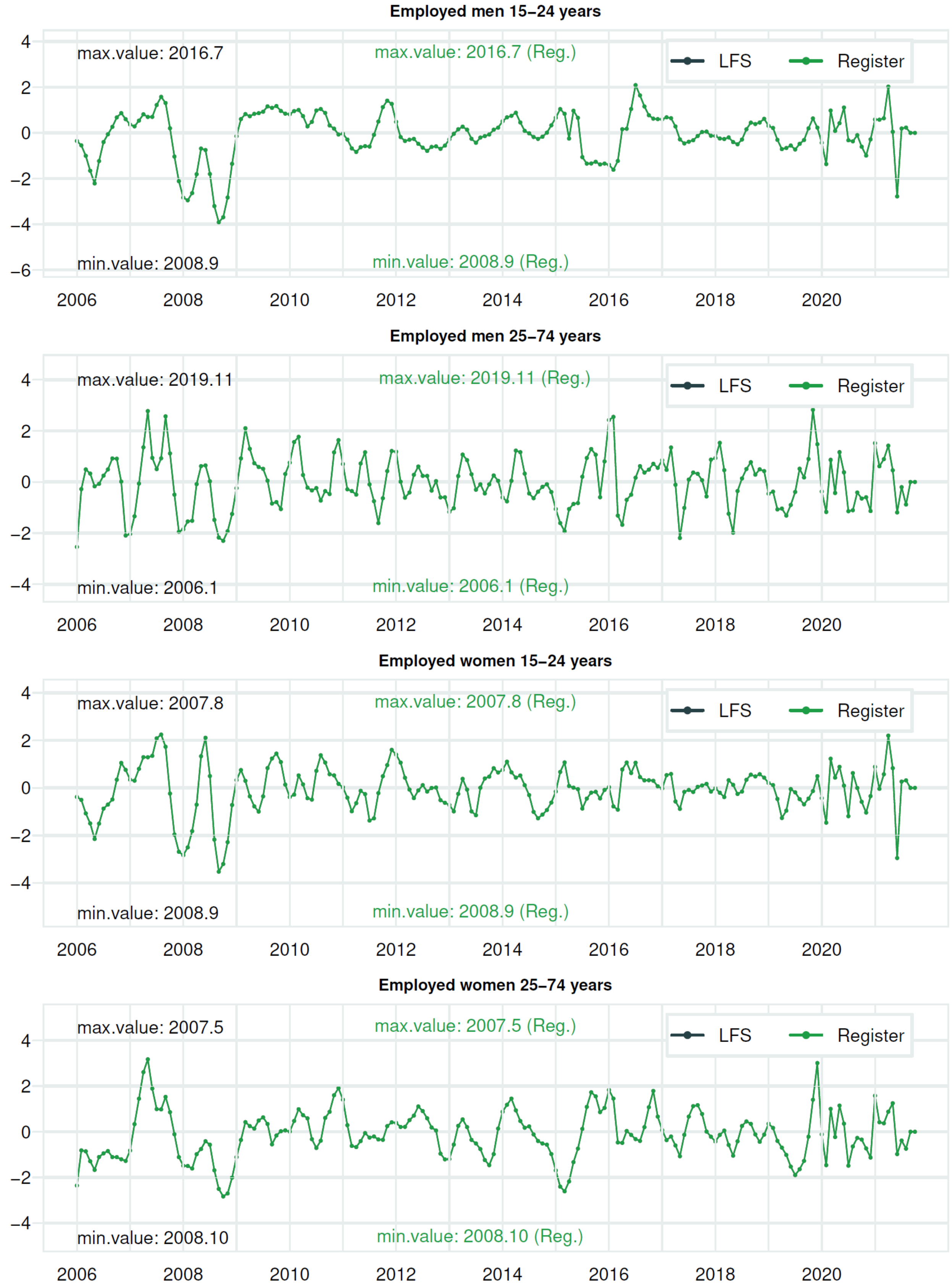
Source: Statistics Norway

Figure B.2 Standardized recursive residuals for unemployed persons for the different LFS-waves and the register variable by sex and age



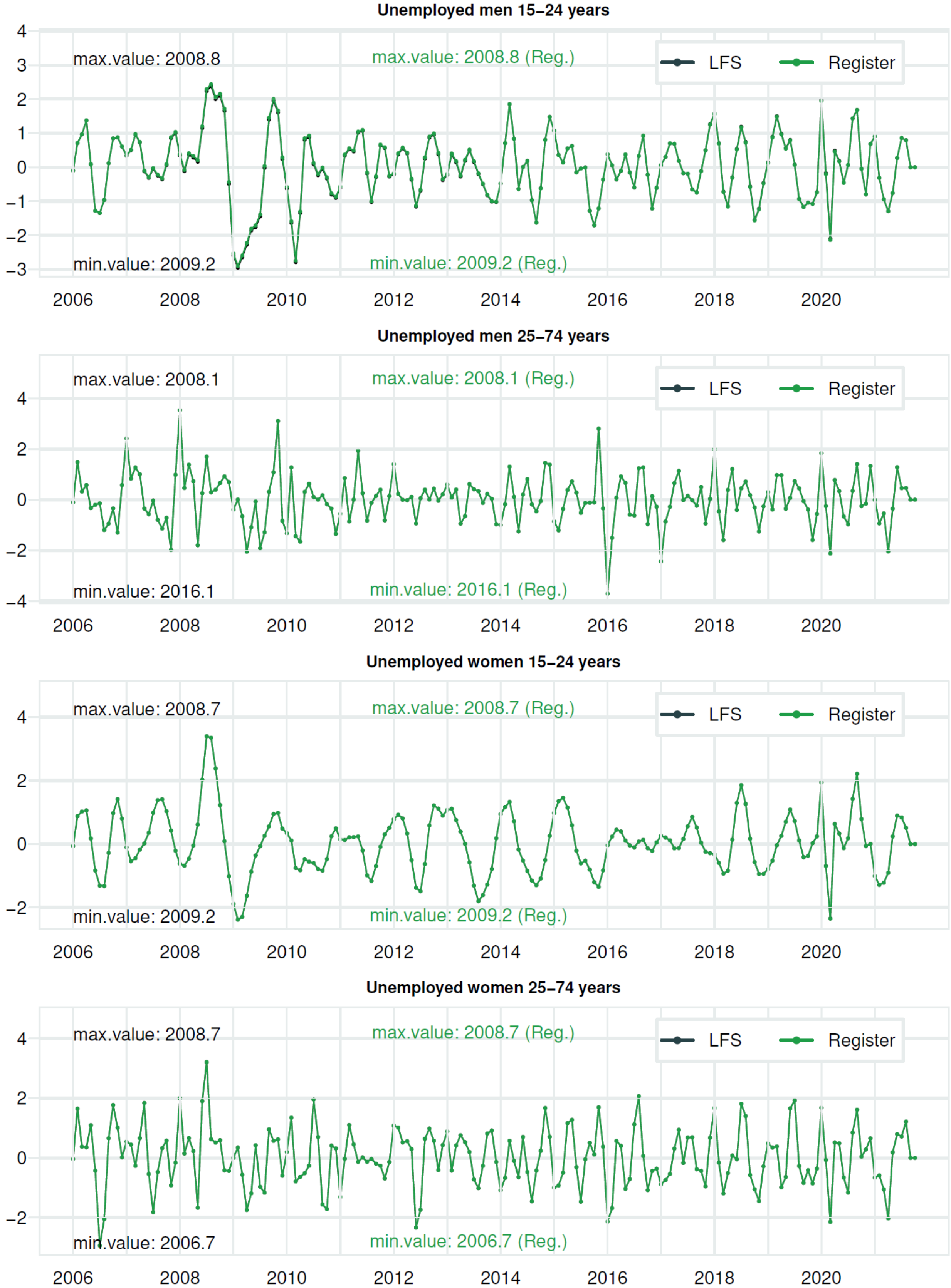
Source: Statistics Norway.

Figure B.3 Auxiliary residuals for slope parameter for employed persons by sex and age[1]



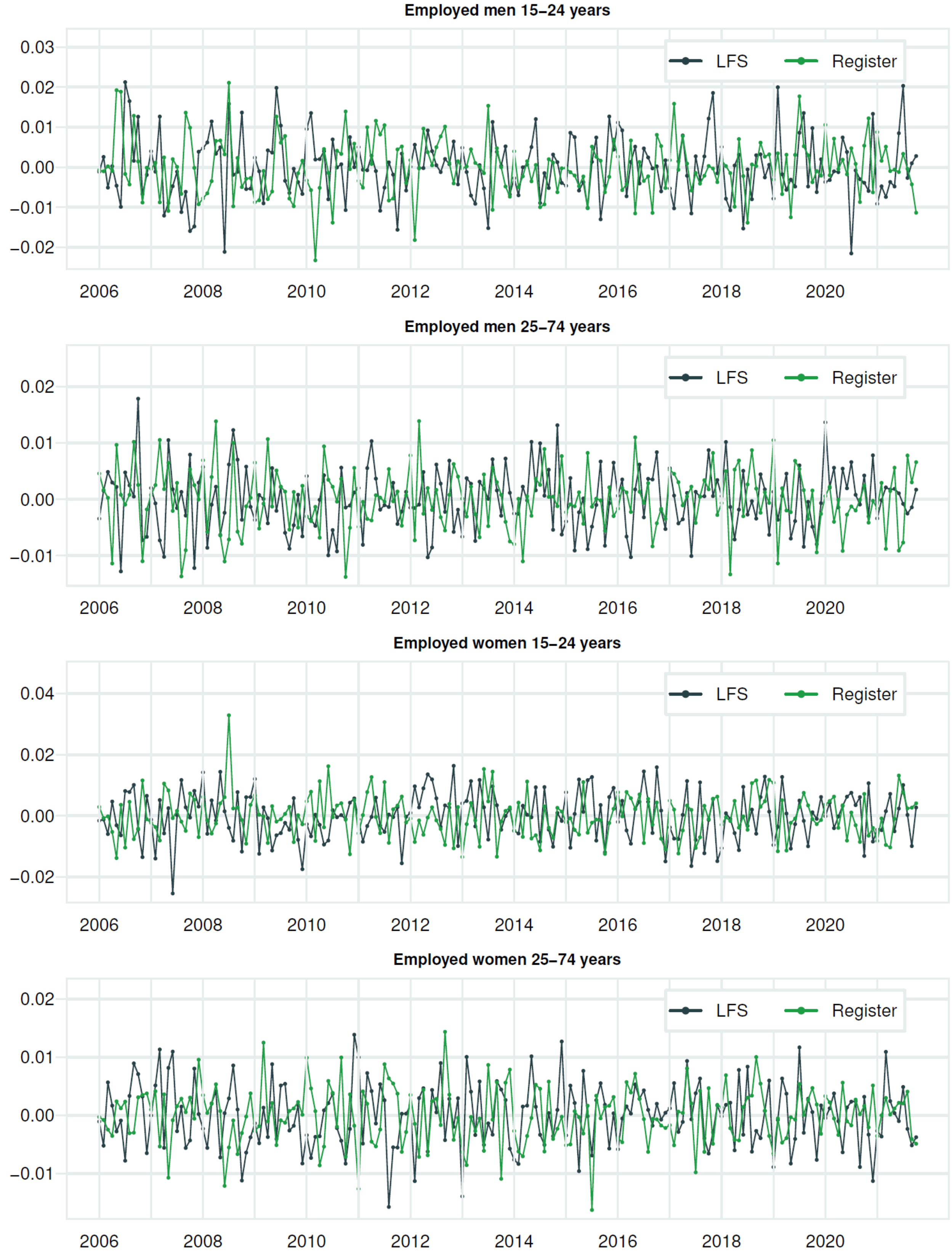
[1] In figure B.3 you can't see the line for LFS, because it is almost identical to the line for Register. The reason for this is that the correlation for the error term of the slope of the trend between LFS and register is equal or almost equal to 1.
Source: Statistics Norway.

Figure B.4 Auxiliary residuals for slope parameter for unemployed persons by sex and age[1]



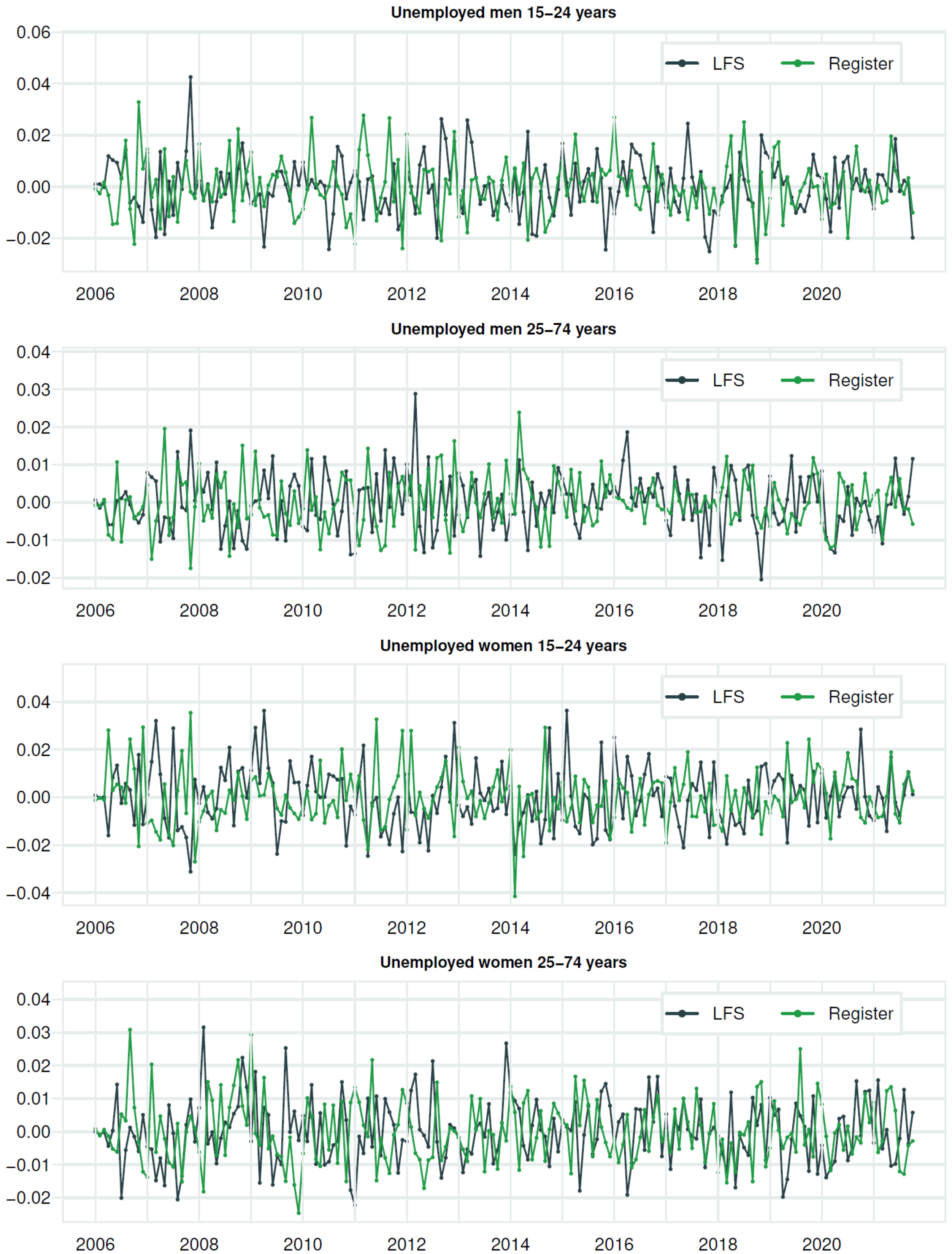
[1] In figure B.4 you can't see the line for LFS, because it is almost identical to the line for Register. The reason for this is that the correlation for the error term of the slope of the trend between LFS and register is equal or almost equal to 1.
Source: Statistics Norway.

Figure B.5 Auxiliary residuals for irregular component for employed persons by sex and age



Source: Statistics Norway.

Figure B.6 Auxiliary residuals for irregular for component for unemployed persons by sex and age

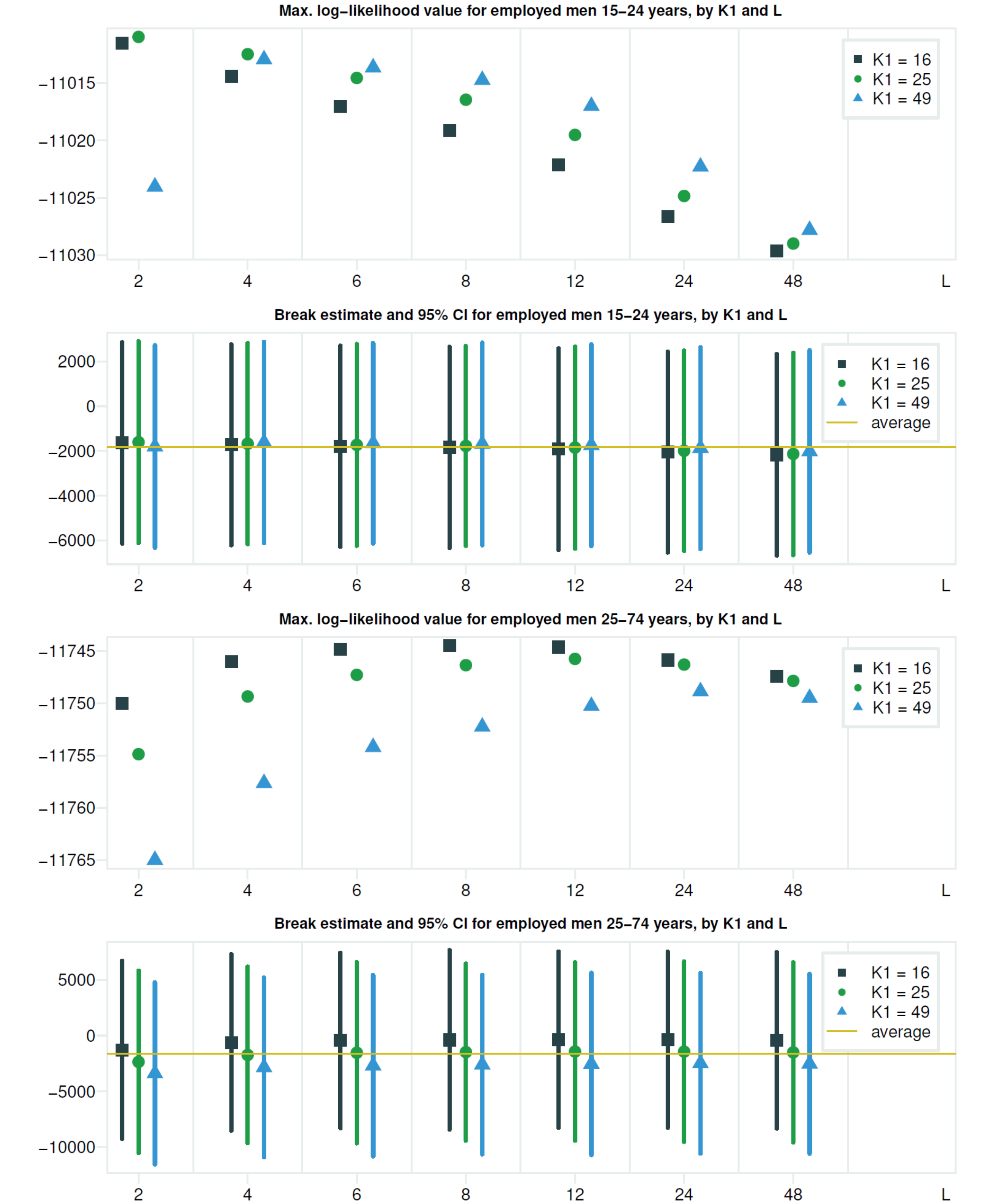


Source: Statistics Norway.

Appendix C: Sensitivity analysis of the break estimates

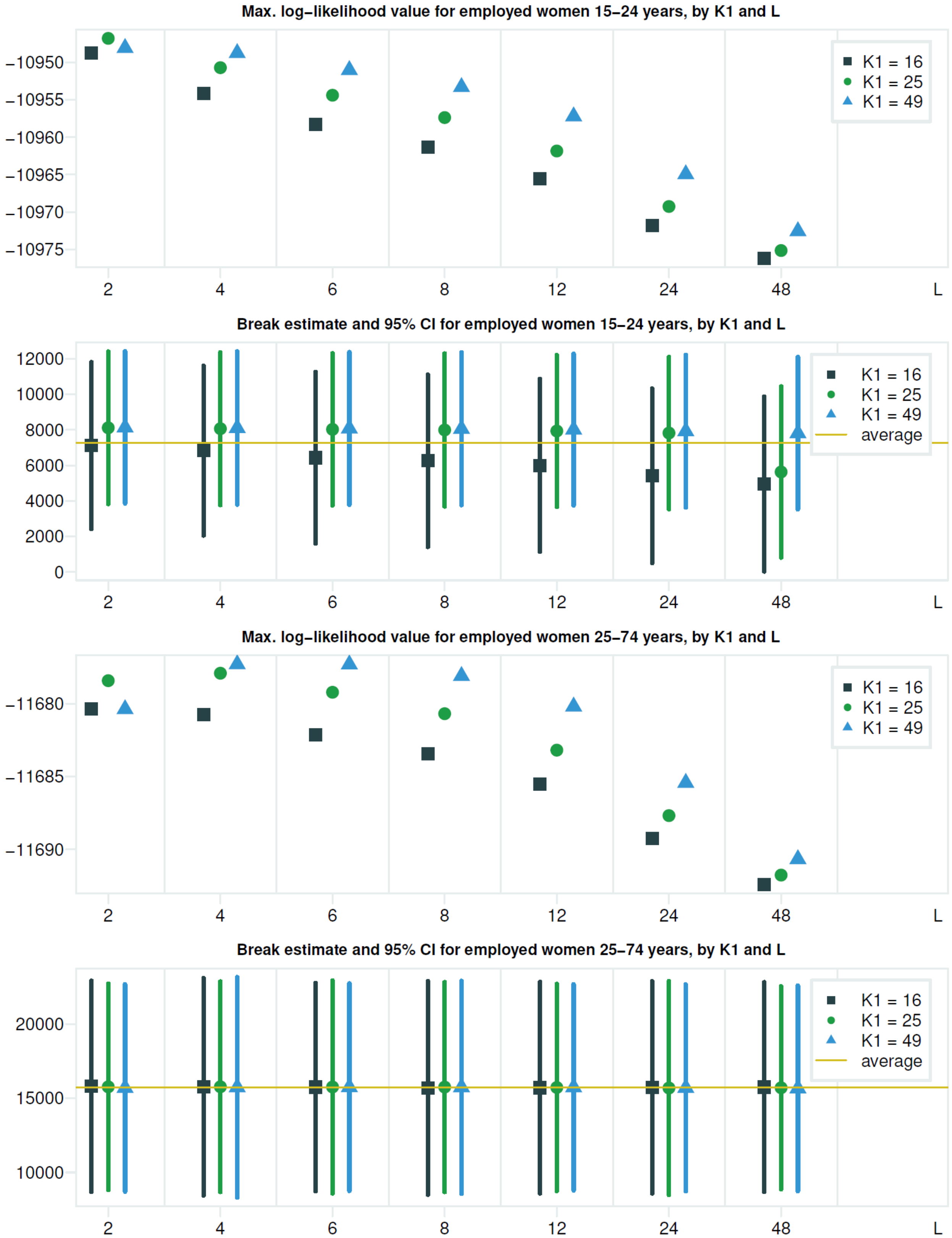
Illustrations of break estimate sensitivity and model fit (log-likelihood) depending on COVID-19 inflation parameter for rescaling of hyperparameters related to the trend are presented here.

Figure C.1 Maximum log-likelihood value (upper panel) and estimated 2021-redesign level shift parameter and 95% confidence interval (lower panel) for employed men by COVID-19 inflation parameter for rescaling of hyperparameters related to the trend and age[1]



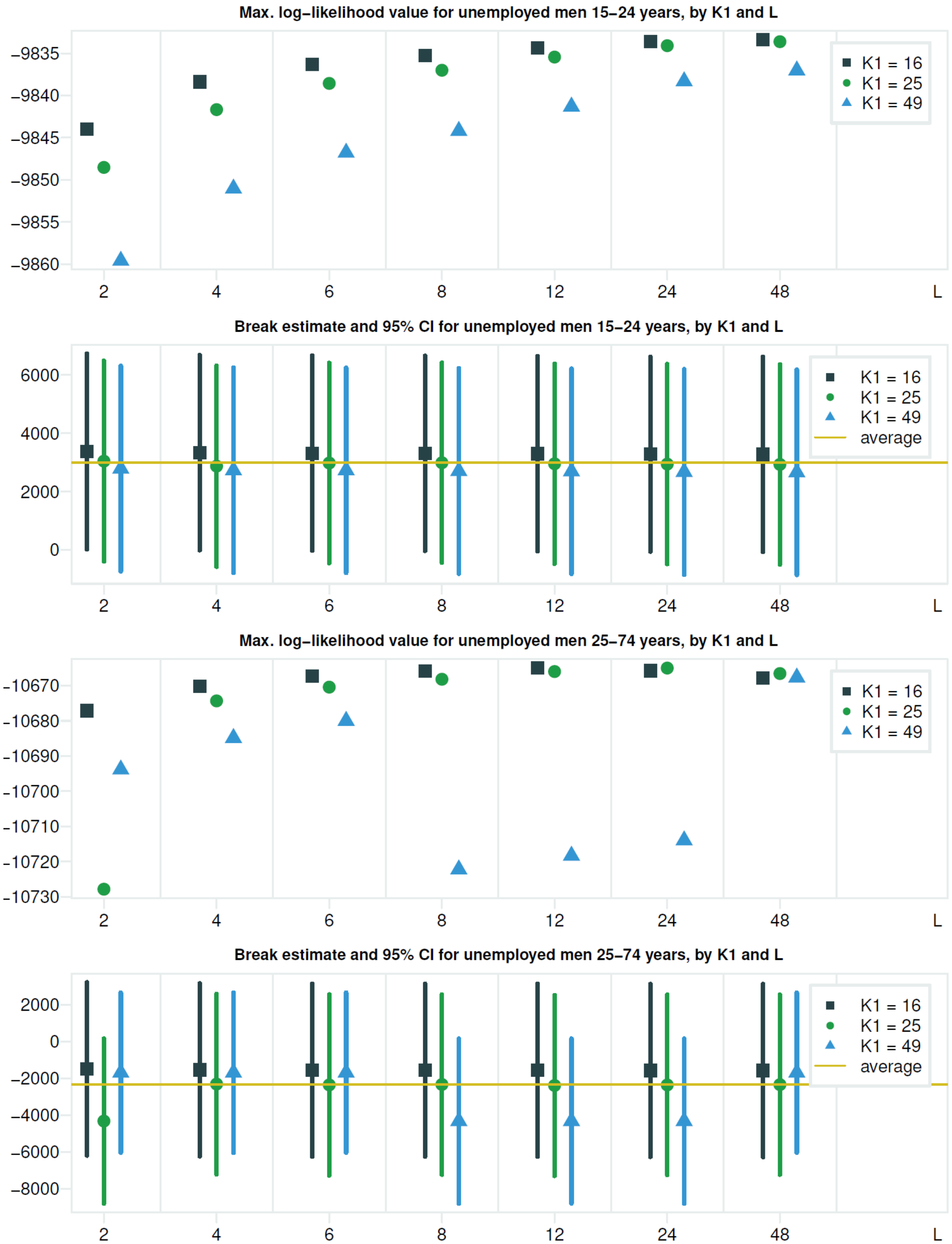
[1] K1 and K2 are COVID-19 inflation parameter for rescaling of hyper parameters related to the trend. K1 is used for the first half of 2020 and K2 thereafter, where K2(K1,L) = (K1 + L-1) / L .
Source: Statistics Norway.

Figure C.2 Maximum log-likelihood value (upper panel) and estimated 2021-redesign level shift parameter and 95% confidence interval (lower panel) for employed women by COVID19-inflation parameter for rescaling of hyperparameters related to the trend and age[1]



[1] K1 and K2 are COVID-19 inflation parameter for rescaling of hyper parameters related to the trend. K1 is used for the first half of 2020 and K2 thereafter, where K2(K1,L) = (K1 + L-1) / L .
Source: Statistics Norway.

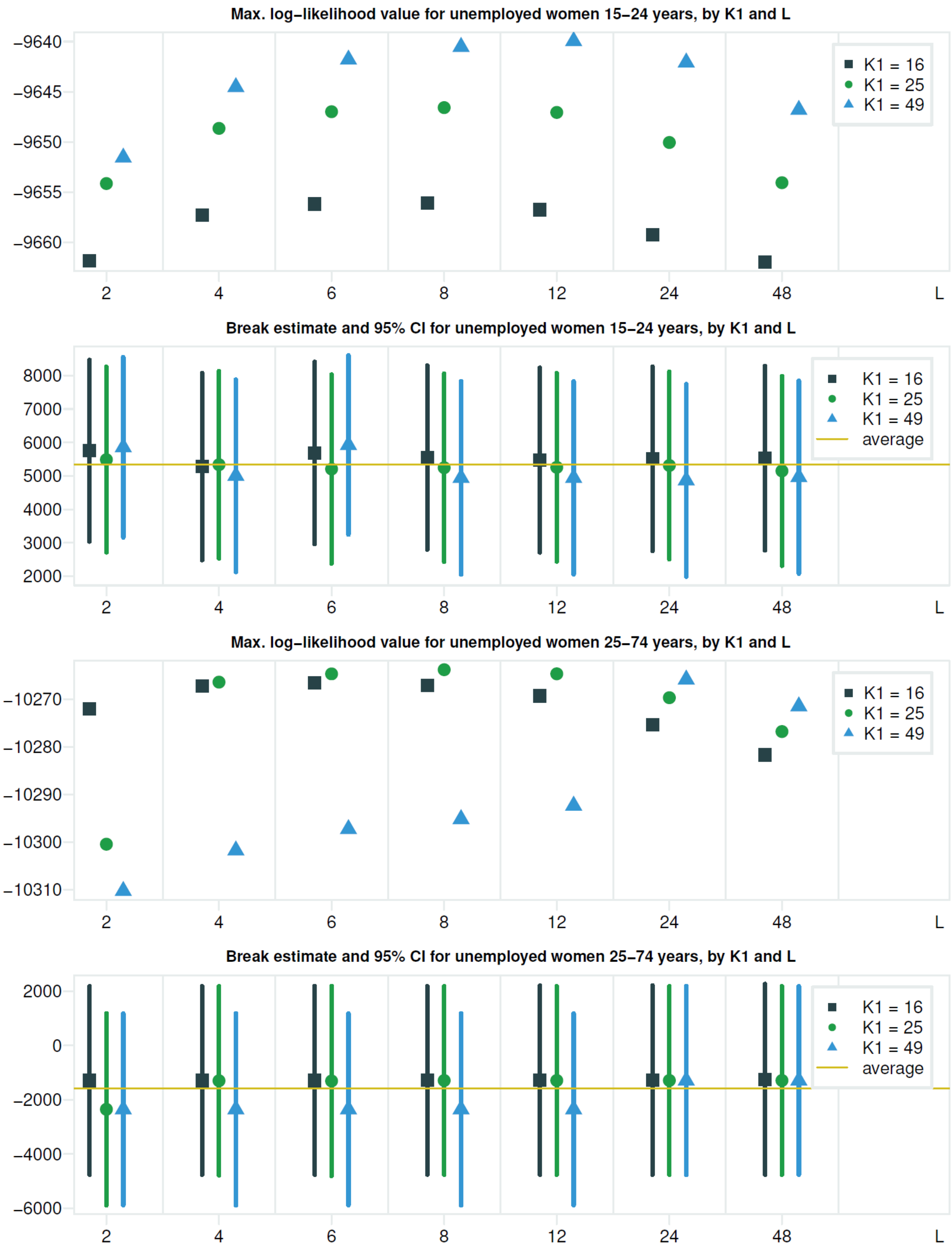
Figure C.3 Maximum log-likelihood value (upper panel) and estimated 2021-redesign level shift parameter and 95% confidence interval (lower panel) for unemployed men by COVID-19 inflation parameter for rescaling of hyperparameters related to the trend and age[1]



[1] K1 and K2 are COVID-19 inflation parameter for rescaling of hyper parameters related to the trend. K1 is used for the first half of 2020 and K2 thereafter, where K2(K1,L) = (K1 + L-1) / L .

Source: Statistics Norway.

Figure C.4 **Maximum log-likelihood value (upper panel) and estimated 2021-redesign level shift parameter and 95% confidence interval (lower panel) for unemployed women by COVID-19 inflation parameter for rescaling of hyperparameters related to the trend and age[1]**



[1] K1 and K2 are COVID-19 inflation parameter for rescaling of hyper parameters related to the trend. K1 is used for the first half of 2020 and K2 thereafter, where K2(K1,L) = (K1 + L-1) / L .
Source: Statistics Norway.

Appendix D: Information from the parallel data collection in 2020Q4

Results even from a small parallel data collection can help a time series model to make more precise and less preliminary estimates of the effect due to a redesign of a survey. Our parallel data collection was designed for intervener training. Thus, the sample is too small to estimate the effects of the 2021 redesign precisely. However, the information can still be used in combination with a time series model to model the effects of the 2021 LFS redesign. This approach is discussed in van den Brakel, Zhang and Tam (2020). This is done by exact initializing the specified 2021 level shift parameter during the estimation. For this purpose, an initial estimate of the level shift parameter and the associated standard error of the level shift is required and tabulated below. These point estimates are the difference in level between population estimates based on new and old LFS surveys. However, we will only use the information in the time series model for wave 1. The reason is that the parallel data collection is for a new sample so that it becomes a kind of first-time interview or "wave 1" estimate with a new questionnaire.

Sampling design for parallel data collection 2020Q4 with the new questionnaire

The population is persons aged 15-89 resident in private households according to our registers before 2020Q4, even though only information for persons aged 15-74 is used here. A stratified random sample of 2,625 persons was selected. 56 strata were used, and the following combination of age groups, region and register-based employment status were used:

- The 6 NUTS2 regions[42] for register unemployed aged 15-74, and
- NUTS2 regions cross-classified with the age groups (15-29, 30-54, 55-66, 67-74) and register status (employees, others except for register unemployed)
- And two extra strata for persons aged 75-89, one for register employees and one for other

Allocation of this sample was also based on previous work[43] and used optimal, multivariate allocation similar to the allocation of the new LFS sample from 2021Q1.

For the parallel sample receiving the new questionnaire, we used a direct post-stratification estimator. Notably, this includes labour market data from our administrative registers 2020M11. The stratification is a partially collapsed cross-classifications, and bring about the following 19 post-strata:

- Status (register employed, register unemployed, other) for persons aged 15-24
- Status (register employed, register unemployed, other) for persons aged 25-54 cross-classified by gender and by level of education (high/low)
- Status (register employed, other) for persons aged 55-74 cross-classified by gender

Due to the small sample size, the simplified estimation method is used for producing the inflation factors (weights) for the wave 1 information from the old questionnaire as well. A simplified estimation method will generally not be able to adjust for as much non-response bias as a more detailed estimation procedure does. However, here it is not the absolute figures that are of interest, but the difference based on the two different questionnaires. Therefore, we used the same simplified estimation method for the weighting of only wave 1 of the old questionnaire 2020Q4. By

[42] For information about the classification of new Norwegian NUTS2 regions valid from January 2020, please see: https://www.ssb.no/en/klass/klassifikasjoner/106/koder

[43] Methodology report about Sampling unit in the Norwegian LFS by Hamre and Jentoft that was the final methodology report of sub-action 9 of a project at Statistics Norway funded by Eurostat for 2017, under Grant agreement 07131.2017.003-2017.597.

doing so, we aim to adjust for about the same amount of non-response bias, and therefore produce good estimates of the differences between the new and old questionnaire.

The results from the parallel data collection in 2020Q4 used in the time series model

Table D.1 Labour market status 4th. quarter 2020 according to the Norwegian LFS by age and sex. Difference in point estimates between the new (2021) questionnaire and the old questionnaire based on wave 1 only, and approximate standard error (Std. err.) [1]

	Employed persons		Unemployed persons	
Gender and age	Difference in point estimates	Std. err.	Difference in point estimates	Std. err.
Male 15-24	15 239	17 892	6 073	9 817
Male 25-74	30 663	20 851	-10 020	15 318
Female 15-24	7 158	16 396	3 813	8 514
Female 25-74	47 087	18 038	-11 894	12 087
Male	45 902	27 475	-3 947	18 194
Female	54 245	24 376	-8 081	14 785
Persons 15-24	22 397	24 268	9 886	12 995
Persons 25-74	77 750	27 571	-21 914	19 512
Indirect total	100 147	36 730	-12 028	23 444

[1] Weighted figures based on the same simplified post-stratification estimator, but with different population figures due to different population limitations before and after the 2021 redesign of the Norwegian LFS. Due to a small sample and no female aged 55-74 years in the sample who answered that they were unemployed, which gives Std. err.=0 and unrealistically low std. err. for the change estimate, we adjust std. err. for the change estimate for the group of unemployed so that the Std. err. for the change estimate relative to the population size is equal to the unweighted average relative Std. err. for the change estimates for the two groups, men aged 55-74 and female aged 25-54.
Source: Statistics Norway.

Table D.1 reports the initial level shift estimates for wave 1 and associated standard errors. The results will not represent the whole level shift estimate projections that come out of the time series model, which will be the average of the final level shift estimates for all 8 waves.

Average level shift estimates from the wave-distributed time series model will also be affected by the length of the time series after the redesign, the results from all 8 waves and register information used as auxiliary variables in the model.

Only selected key figures for wave 1 based on the small sample are reported here. The new LFS will provide a total of 100,000 more employed (point estimate for wave 1) than the old LFS. The standard error of this estimate is 37,000, so it seems to be a significant increase.

All four main subgroups (gender crossed with age over/under 24 years) show more employed persons with a new LFS, but only for females aged 25-74 years is the change significant.

The change in the employment figures for young men is most surprising, an increase of 15,000 (+ 9.5%), despite the fact that conscripts were not counted as employed in the new LFS as they were in the old LFS. However, as the standard error for this estimate is as much as 18,000, the resultat is not significant and we can not rule out that there has been a slight decline.

The new LFS will provide a total of 12,000 fewer unemployed (point estimate) than the old LFS. Still, the standard error is 23,000, so the estimate is not significantly different from zero. The new LFS seems to indicate more unemployed people under the age of 25 and fewer unemployed over 24, but all these estimates are insignificant.

Appendix E: Results from model without exact initialization of level shift parameter

Table E.1 Average smoothed 2021-redesign level shift parameter estimates and standard error (Std. err.) for employed and unemployed persons, by gender and age, based on a model without exact initialization of the wave 1 estimate based on information from parallel data collection 2020Q4, but with register- and LFS-data ending at 2021M8

	Employed persons		Unemployed persons	
Gender and age	Estimate	Std. err.	Estimate	Std. err.
Total indirect by 4 domains (gender : 2 age grp.)	8 506	6 999	2 606	4 397
Male and Female aged 15-24 (indirect by gender)	8 419	3 439	7 568	2 425
Male and Female aged 25-74 (indirect by gender)	87	6 096	-4 962	3 667
Male (indirect by age, more / less than 24)	-8 483	5 064	1 514	3 320
Female (indirect by age, more / less than 24)	16 989	4 832	1 092	2 883
Male aged 15-24	-520	2 473	1 977	1 902
Male aged 25-74	-7 963	4 419	-463	2 721
Female aged 15-24	8 939	2 390	5 591	1 505
Female aged 25-74	8 050	4 199	-4 499	2 459

Source: Statistics Norway.

Without using information from the parallel sample, the break estimates (based on a smooth trend model with data up to 2021M8) for employed persons are quite a bit lower and the standard errors are higher than with the inclusion of the extra information. For unemployed persons, the difference is smaller. Here, the higher standard errors also reflect that the model estimates only utilize data ending at 2021M8.

The COVID-19 pandemic created additional uncertainty. This spoke in favour of utilizing all available information, even though the parallel data capture was only for a small sample and was carried out with training as the purpose.

Table E.2 Smoothed 2021-redesign level shift parameter estimates and standard error (Std. err.) for employed and unemployed persons, by gender, age and wave, based on a model without exact initialization of the wave 1 estimate based on information from parallel data collection 2020Q4, but with register- and LFS-data ending at 2021M8

		Male				Female			
		Employed persons		Unemployed persons		Employed persons		Unemployed persons	
Age and wave		Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.
15-24	**1**	**-4 871**	**7 059**	**2 761**	**5 123**	**24 513**	**6 830**	**6 880**	**4 044**
	2	7 530	6 769	1 360	5 224	15 019	6 422	-2 280	4 024
	3	1 747	6 826	6 951	5 364	9 773	6 683	7 774	4 198
	4	1 358	6 845	-4 032	5 418	6 982	6 813	4 958	4 344
	5	1 199	6 881	3 555	5 400	-696	6 665	6 829	4 306
	6	-8 403	6 988	4 816	5 446	4 439	6 751	1 930	4 291
	7	3 445	7 171	1 121	5 542	329	6 625	11 145	4 289
	8	-6 167	7 399	-713	5 501	11 151	7 252	7 488	4 527
	Average	-520	2 473	1 977	1 902	8 939	2 390	5 591	1 505
25-74	**1**	**-47 205**	**17 248**	**8 338**	**8 746**	**-32 835**	**16 879**	**-3 190**	**8 499**
	2	-14 447	12 781	-8 991	7 824	14 831	12 546	-3 384	6 843
	3	-12 976	11 391	-4 775	7 569	17 280	10 240	-2 820	6 642
	4	3 410	11 231	-5 083	7 488	3 710	10 429	-4 116	6 600
	5	-9 313	11 298	-2 167	7 432	16 116	11 249	-1 137	6 639
	6	-1 049	11 083	9 495	7 495	12 493	10 364	-12 243	6 680
	7	7 916	11 330	-4 504	7 460	23 154	10 722	-2 341	6 720
	8	9 963	12 421	3 982	7 472	9 647	11 129	-6 758	6 808
	Average	-7 963	4 419	-463	2 721	8 050	4 199	-4 499	2 459

Source: Statistics Norway.

Since the information from parallel data collection for 2020Q4 only is used in the time series model for wave 1, the difference in standard errors compared to the table above is largest for wave 1, as expected.

Appendix F: Preliminary 2021-redesign level shift estimates

Here we present some of the preliminary 2021-redesign level shift estimates.

Table F.1 Preliminary average smoothed 2021-redesign level shift parameter estimates and standard error for employed and unemployed persons, by gender and age, based on information from parallel data collection 2020Q4, and register and LFS data ending at 2021M9

	Employed persons		Unemployed persons	
Gender and age	Parameter estimate	Standard error	Parameter estimate	Standard error
Total indirect by 4 domains (gender : 2 age grp.)	27 710	6 243	6 123	3 780
Male and Female aged 15-24 (indirect by gender)	8 732	3 222	8 872	2 260
Male and Female aged 25-74 (indirect by gender)	18 978	5 347	-2 749	3 030
Male (indirect by age, more / less than 24)	3 597	4 526	1 184	2 986
Female (indirect by age, more / less than 24)	24 113	4 300	4 939	2 317
Male aged 15-24	564	2 326	2 880	1 747
Male aged 25-74	3 033	3 882	-1 696	2 422
Female aged 15-24	8 168	2 230	5 992	1 434
Female aged 25-74	15 945	3 677	-1 053	1 820

Source: Statistics Norway

Based on data ending at 2021M9, the preliminary break estimates for the 2021-redesign level shift for employed persons were slightly higher, while there were small differences for unemployed persons.

The revisions are due to both more data and better models where the COVID-19 inflation parameter for rescaling of hyperparameters related to the trend are fine-tuned again.

Preliminary break estimates based on data ending at 2021Q2 were about the same as the final results for employed persons, but the preliminary break estimates for unemployed were about 3,000 higher, which is not a large difference compared to the standard error.

Appendix G: Methodological summary regarding the correction for breaks in time series for the website Statistics Explained [44]

In 2021 The Norwegian LFS went through a substantial redesign in accordance with the new regulation for integrated European social statistics (IESS). To ensure coherent labour market time series for the main indicators, the redesign's impact is modelled to make back-calculated estimates adjusted for possible breaks due to the 2021 LFS-redesign.

We pursue a structural time series approach in the tradition of Pfeffermann (1991), van den Brakel et al. (2009, 2015) and Elliott and Zong (2019). Breaks are estimated for the number of employed and unemployed persons.

In addition to the 8 waves with monthly LFS data for employed and unemployed persons, we also include auxiliary time series for registered number of employees and unemployed respectively in the preferred models.

The time series for register employees are pre-adjusted for discontinuity related to a transition of registers in 2015. The auxiliary variable based on the unemployed register at the employment office is "layoff-harmonized" by subtracting individuals that are temporarily laid off for less than 90 days from the number of persons that are registered as unemployed. We use a 2-month moving average of this auxiliary variable. By making these two adjustments, the auxiliary variable has a stronger correlation with the LFS-unemployment in our model, particularly during the COVID-19 pandemic.

The structural time series model contains unobserved components for trend, seasonality and irregularity, all of which are assumed to be the same for all waves. A smooth trend model is used. In addition, we account for rotation group bias and the autocorrelation structure brought about by the rotating panel design, as well as sampling error heterogeneity caused by changes in the (net) sample sizes over time, due to changing non-response rates, whether the month contains 4 or 5 survey weeks and a change in the allocation of the sample for different groups gradually rolled in quarter by quarter in 2021.

The auxiliary time series are decomposed into components for trend, seasonality and irregularity. Information from the auxiliary variables is used to obtain more precise break estimates by allowing the two trend components' error terms to be correlated.

To correct for the effect of the COVID-19 pandemic, we allow the hyperparameters for the trend to be higher during the pandemic. We do this to counteract the contaminating effects the pandemic has on the estimate of the structural break following the redesign of the LFS.

[44] This Methodological summary, with minor adjustments, have been sent to Eurostat for publication at their website: https://ec.europa.eu/eurostat/statistics-explained/index.php?title=EU_labour_force_survey_-_correction_for_breaks_in_time_series&stable=0&redirect=no. Due to the assumption by Eurostat that there is no break in the target population, we informed Eurostat about the following regarding our correction input: As from 2021, Norway has changed the delimitation of the population in accordance with IESS regulation, by not including persons resident in non-private households. Therefore, our population figures prior to 2021 are not comparable to the new population figures, so the assumption that there are no breaks in the population figures is not valid. Therefore, calculating employment proportions or residual determining persons outside the labour force based on our break adjusted employment and unemployment backcasts, will not produce correct break adjusted employment proportions or figures for persons outside the labour force, until new population figures are delivered. Also, deriving other break adjusted indicators where it is assumed that there is no break in the population figures may be problematic. Such figures, employment proportions and other derived figures using the old population figures, must be flagged/labelled as with (possible) breaks, due to change in the population definition.

The effect of the redesign is modelled as separate level shifts for each wave. The final break estimates are based on modelling time series from 2006M1-2021M10. Information from a parallel survey with the new questionnaire carried out in the last quarter of 2020 for a small sample is also utilized in the time series model. Technically, the break parameter related to wave 1 is initialized exactly utilizing information from the parallel survey.

The time series are modelled for four main domains: gender cross-classified by age 24 and below/25 and above. The domain-specific break estimates are given as the average of the estimates of the break parameters for the 8 waves. These break estimates are divided into sub-groups using monthly time-varying sub-group splitting factors assuming a proportional distribution of the breaks.

The break estimates relative to the population are used to produce back-calculated monthly and quarterly time series for main indicators for the years 2006-2020.