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Abstract:
The labour force surveys (LFSs) on all Eurostat countries underwent a substantial redesign in January 2021. To ensure coherent labour market time series for the main indicators in the Norwegian LFS, we model the impact of the redesign. We use a state-space model that takes explicit account of the rotating pattern of the LFS. We also include auxiliary variables related to employment and unemployment that are highly correlated with the LFS variables we consider. The results of a parallel run are also included in the model. This paper makes two contributions to the literature on the effects of LFS redesign. First, we suggest a symmetric specification of the process of the wave-specific effects. Second, we account for substantial fluctuations in the labour force estimates during the Covid-19 pandemic by applying time-varying hyperparameters. Likelihood-ratio tests and examination of the auxiliary residuals show the latter to be warranted.

Keywords: State-space models, Auxiliary information, Labour market domains, Level shifts, Covid-19, Norway

JEL classification: C32, C51, C83, J21.

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Sammendrag

Tidsserier fra Arbeidskraftsundersøkelsene (AKU) er av stor interesse for mange ulike etater og individer i Norge. De er konstruert fra bakenforliggende roterende paneldata for individer. Fra tid til annen skjer det endringer i utvalgsundersøkelsene som krever justeringer av tidsseriene for at en sammenligning over tid skal være informativ. Slike justeringer omtales som bruddjuste-ringer. I begynnelsen av 2021 skjedde flere endringer som ga opphav til behov for bruddjuste-ringer. En oversikt over disse gis i manuskriptet.

Dataene er månedlige, og vi bruker data fra og med januar 2006 til og med oktober 2021. Vi ser både på sysselsatte og arbeidsledige, og vi modellerer ulike undergrupper som er delt inn etter kjønn og alder. For hver undergruppe betraktes 9 tidsserier hvorav 8 er de såkalte utvalgsbølgene fra AKU, mens den siste er en registervariabel. I en gitt måned vil utvalget på grunn av rota-sjonsdesignet være sammensatt av individer som er med før første gang, for annen gang osv. inntil åttende og siste gang.

Vi gjennomfører bruddjustering innenfor rammen av såkalte (multivariate) strukturelle tidsse-riemodeller der vi spesifiserer disse som tilstandsmodeller. I strukturelle tidsseriemodeller skiller en mellom ulike latente komponenter som har en klar fortolkning. Vi har med komponenter for trend, sesong og irregularitet. Disse komponentene er antatt å være de samme for de åtte utvalgs-bølgene, mens det er egne slike komponenter for registervariabelen. En viktig antagelse i analy-sen er at trenden for AKU-variablene og registervariabelen er korrelerte. Ved siden av disse tre komponentene har vi også med to komponenter som kun inngår for utvalgsbølgene og ikke for registervariabelen. Dette er bølgespesifikke latente effekter og en komponent som fanger opp en autokorrelasjonsstruktur i utvalgsfeilen som følger av rotasjonsdesignet. Selve bruddeffekten er modellert som et nivåskift som inntreffer januar 2021. Den tillates å variere mellom bølgene. Bruddeffekten berører ikke registervariabelen, og det er dette som gjør at en klarer å kvantifisere effekten av bruddet.

Det at bruddet på grunn av redesign av AKU har funnet sted samtidig med en pandemi (Covid-19) er utfordrende. Vi har forsøkt å ta hensyn til dette ved å tillate at trendene, både til AKU-variablene og registervariabelen har vært mer volatile under pandemien. Dette har blitt gjort ved å innføre tidsvarierende hyperparametre i spesifikasjonen av trendene. Volatiliteten tillates å være sterkere fra og med starten av 2020. Vi har skilt mellom 2 underperioder der en tar hensyn til at volatiliteten var sterkere i første halvår 2020 enn i de etterfølgende måneder inntil oktober 2021, som er siste måned som er med i undersøkelsen.

Vi finner at det å ta hensyn til endret volatilitet i trendkomponentene har noe å si for bruddesti-matet. Basert på bruddestimatene for de ulike undergruppene kan vi avlede et totalt bruddestimat for henholdsvis sysselsatte og ledige. For sysselsatte finner vi et bruddestimat for januar 2021 på i overkant av 24.000 individer. Det er imidlertid stor variasjon mellom de ulike undergruppene som utgjør totalen. Det er resultatene for kvinner som dominerer når det gjelder bruddestimatet for sysselsetting. Resultatene for menn er ikke signifikant forskjellige fra null. Det totale brudde-stimatet for arbeidsledige er på i underkant av 5.500 individer, men det er ikke signifikant for-skjellig fra null. Også for de arbeidsledige er det betydelig variasjon mellom undergruppene som til sammen utgjør totalen. Det er den yngste aldersgruppen, som utgjøres av individer mellom 15 og 24 år, for begge kjønn som trekker estimatet opp. Her finner en positive signifikante estima-ter, mens estimatene for den eldste aldersgruppen, som utgjøres av de mellom 25 og 74 år, begge er små, negative og ikke signifikante.

1. Introduction[1]

Time series from labour force surveys (LFS) that describe the situation in the labour market are important for many users. These series provide essential information for fiscal and monetary policy and centralized wage bargaining in Norway, either directly or indirectly through the national accounts. Therefore, they must be defined consistently across time, as it is otherwise difficult to interpret them. From time to time, it is necessary to redesign the surveys, for instance, in connection with international regulations. Such changes require correcting time series to make them comparable over time. How best to quantify and implement such corrections depends on the information at hand: for instance, whether one has parallel surveys or auxiliary variables at one's disposal.

From the beginning of 2021, the Norwegian LFS went through a substantial redesign in accordance with the new regulation for integrated European social statistics (IESS). There is a modified questionnaire, where question sequences, formulations and answer alternatives have changed. The target population was changed from covering all registered residents aged 15-74 to registered residents aged 15-89 in private households. At the same time (and not required through IESS), Statistics Norway changed the sampling design. The sampling unit changed from nuclear family to person, and the sample is now stratified according to the characteristics of the persons. Due to the sampling unit's change, Statistics Norway no longer allows other family or registered household members to answer on behalf of the person anymore.

The current paper quantifies the structural breaks in the main LFS time series brought about by the substantial redesign of the Norwegian LFS. The analysis is carried out within a structural time series framework using state-space models on monthly data from January 2006 (2006M1) to October 2021 (2021M10). The paper looks at persons aged 15-74, since they are the age group for which we have data both before and after the LFS redesign. We follow the tradition introduced by Pfeffermann (1991) and further developed by, e.g., van den Brakel and Krieg (2009, 2015).

The Norwegian LFSs follow a rotating design, whereby each respondent participates 8 times over a two–year period, making it possible to divide the sample into 8 waves. The modelling strategy follows a disaggregated approach in that the modelling is conducted in different domains by modelling the 8 waves jointly. The aggregated figures are derived from this disaggregated information. Using this approach, we account for the different domains being heterogeneous, which influences aggregate

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[1] A more extensive documentation of the structural break estimates in the Norwegian LFS is available in Hamre et al. (2022).

behaviour. We consider four domains by distinguishing between young men and women (15-24 years), and ‘older’ people (25-74 years) of both sexes.

We model time series for both employed and unemployed persons. Besides the wave information, we 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 a single auxiliary variable in conjunction with each estimation. Thus, we consider modelling a vector with 9 elements, where 8 are from the LFS, and 1 is from the register.

The modelled time series depends on different components. The time series for the 8 waves are assumed to share a common trend component, a common seasonal component and a common irregular component. The auxiliary time series has separate trend, seasonal and irregular components. We allow for correlation between the two trend components but assume that the correlations between the seasonal and irregular components are zero. The assumption concerning the trend is essential because this is the only channel through which the auxiliary variables influence the estimated hyperparameters and extracted components that one ends up with for the LFS time series. The correlation must be sizeable, and the later empirical analysis shows that this is the case.

We expect some persistence in the labour market status of a person. If a person was employed last time she was interviewed in the LFS, she is also more likely to be employed now. This persistence will lead to autocorrelation in the survey errors. Our analysis takes account of such autocorrelation in survey errors stemming from the survey's design. We pre-estimate the autocorrelation parameters using SURE models and plug them into the overall model.

We also apply information from a small parallel survey carried out in the last quarter of 2020. This parallel survey produced a priori information on the effect of the structural break in the time series model. The time-invariant parameters related to the structural break are incorporated into the state vector. Whereas the structural break parameters related to waves 2-8 are initialized with a diffuse prior, the initial distribution of the structural break parameter related to wave 1 follows from the information from the parallel survey.

This paper makes two contributions. First, it suggests symmetric treatment of time-varying wave-specific effects (also referred to in the literature as rotating group biases). Second, we use time-varying hyperparameters in a model for quantifying structural breaks due to survey redesign.

In order to identify all components, we must impose some normalization on the wave-specific effects. In contrast to Statistics Netherlands, which measures the wave-specific effects relative to the first wave (see van den Brakel and Krieg, 2009, 2015), we follow Elliott and Zong (2019) and assume that the wave-specific effects sum to zero. However, in contrast to Elliott and Zong (2019), we do this in a symmetric way in which we do not treat one wave as residual, thereby placing less weight on it.

The Covid-19 pandemic made estimating the effect of the new design more challenging. van den Brakel et al. (2022) consider a similar problem for generating monthly LFS statistics for the Netherlands based on a state-space model. They suggest allowing for higher hyperparameter values for the trend in order to counteract the effect of the shock represented by the pandemic. When estimating the effects of the structural break due to the redesign, we use the same approach in order to accommodate the large fluctuations in the labour market. Furthermore, we show how important this is by comparing the effects with those resulting when we fail to take account of the larger labour market fluctuations during the Covid-19 pandemic.

In specifying the model, we emphasized having a simple model with relatively few hyperparameters. The modelling of the two trend components involves only three hyperparameters, and the two trigonometric seasonal components involve only two parameters. Also, the wave-specific effects involve only one variance.

The remainder of this paper is organized in the following way: Section 2 describes the redesign of the Norwegian LFS and presents the data used in the analysis. This section describes how the monthly wave series are constructed to obtain estimates at population level. The section also presents the redesign of the survey in 2021. Finally, this section provides information about the register data used. Section 3 presents the time-series model we use to estimate the effects of the structural break due to the redesign. We comment on issues related to the state-space model used for estimation. This section also covers how we handle the redesign of the survey and how we take account of the extensive labour market fluctuations during the Covid-19 pandemic. In Section 4, we report our empirical results. Here, we also compare our empirical results with those from a model specification that does not take account of higher fluctuations in the labour market during the Covid-19 pandemic. Section 5 provides some conclusions. In one of the appendices, we provide a detailed specification of our state-space model.

2. About the data

2.1. The Norwegian Labour Force Survey (LFS)

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

The Norwegian LFS has a rotating panel design where the same selected people are requested to respond for several quarters. Since 1996, participants have been requested to respond every 3 months, for a total of 8 consecutive quarters. In each quarter, 1/8 of the sample leaves the survey and an equivalent number of new interviewees are included for the first time. First-time interviewees constitute 1, those interviewed for the second time wave 2, and so on. Those interviewed for the last time are thus wave 8.[2]

The responses from the LFS participants are assigned weights based on how representative they are of the total population. These weights are used to estimate the LFS variables. The estimation procedure for the Norwegian LFS is a one-step multiple-model calibration based on monthly LFS and register data. The method uses register data for employment status, age, sex, NUTS2 region, immigration background, education level, family size, and marital status. The method is described further in Oguz-Alper (2018); see also Nguyen and Zhang (2020).

Let w_i be the calibrated weight for person *i*, and let z_i be an indicator taking the value 1 if person *i* has a particular labour market status, e.g., is unemployed, and 0 otherwise.[3] The estimate for the number of persons in a domain having this working market status, for example being unemployed, is then given as

(1) $$y = \sum_{i \in s} w_i \, z_i.$$

[2] The non-response rate in the Norwegian LFS varied from 14 to 21 percent in the years 2016-2020, see Eurostat (2022). Eurostat (2022, Table 4.5) reports non-response rates of the member states of the Europen Union, three EFTA countries (including Norway) and four candidate countries. The rates are not comparable as the magnitude of non-response are based on household units for most countries. For Norway, like Denmark, Estonia, Luxembourg, Finland, Sweden, Iceland, and Switzerland, the figures are for non-response at an individual level. Of these countries, Norway has the lowest non-response rate, while Switzerland has the second-lowest non-response rate at around 20 percent. The majority of other countries that calculate the non-response rate in the same way as Norway have a non-response rates of 30-50 percent.

[3] To simplify the notation, we have omitted subscripts for time and domain in all variables included in (1) and (2).

We apply the same weights as for the overall estimates to make the wave-specific estimates for employment and unemployment used in this analysis. Let δ_i^j be an indicator, where $\delta_i^j = 1$ if person *i* is in wave *j* and $\delta_i^j = 0$ otherwise. Then the estimate for the number of, say, unemployed persons in a domain based on the respondents in wave *j* only, is given by

$$(2) \qquad y^j = \frac{\sum_{i \in s} w_i}{\sum_{i \in s} w_i \delta_i^j} \sum_{i \in s} w_i \, z_i \delta_i^j .$$

The first line in Table 1 reports the mean of the number of employed people according to the LFS given by (1) for two subperiods, i.e., for the period 2006M1-2019M12 and the remaining sample period 2020M1-2021M10. We also provide estimates for four domains. These domains are based on two age groups for both sexes. We distinguish between young persons aged 15-24 years and persons aged 25 years or older. Most of the employed individuals of both sexes are in the 'older' age group. This is no surprise, as these are also the two biggest domains in the population.

Similarly, the first line in Table 2 reports the mean value of unemployed people given by (1) for the same time periods and domains are as used in Table 1. When considering the estimates for LFS unemployment, we also see that most are in the oldest age groups. However, the unemployed are more evenly distributed amongst the groups. Thus, the unemployment rate – which is not reported in the tables – is lower for the older age groups.

Tables 1 and 2 also report the wave-specific estimates according to (2). The wave-specific effect is especially pronounced for wave 1 for all domains, with lower employment and higher unemployment than the average.

In the lower parts of Tables 1 and 2, we report the empirical variance of the 12-month growth in LFS employment and unemployment for each wave and for the mean of the waves. The variance for a specific wave is substantially larger than for the variance of the mean of the waves. As noted for the means above, the variances of the register variables are less than those of the LFS variables.

Table 1 Descriptive statistics. Employed persons

	All domains jointly		Males 15-24 years old		Males 25-74 years old		Females 15-24 years old		Females 25-74 years old	
	Until 2019	From 2020	Until 2019	From 2020	Until 2019	From 2020	Until 2019	From 2020	Until 2019	From 2020
$mean(y_t)/10^6$	2.570	2.735	0.168	0.168	1.188	1.277	0.164	0.166	1.049	1.124
$mean(y_t^1)/10^6$	2.546	2.670	0.163	0.169	1.184	1.254	0.157	0.163	1.042	1.085
$mean(y_t^2)/10^6$	2.571	2.724	0.167	0.173	1.189	1.272	0.165	0.171	1.050	1.108
$mean(y_t^3)/10^6$	2.573	2.733	0.168	0.172	1.189	1.263	0.167	0.171	1.050	1.127
$mean(y_t^4)/10^6$	2.575	2.731	0.169	0.163	1.190	1.280	0.165	0.166	1.051	1.121
$mean(y_t^5)/10^6$	2.579	2.736	0.170	0.167	1.192	1.274	0.165	0.163	1.052	1.131
$mean(y_t^6)/10^6$	2.575	2.750	0.171	0.162	1.189	1.287	0.166	0.165	1.050	1.137
$mean(y_t^7)/10^6$	2.568	2.770	0.172	0.174	1.185	1.281	0.165	0.167	1.047	1.147
$mean(y_t^8)/10^6$	2.583	2.753	0.170	0.168	1.193	1.286	0.164	0.162	1.056	1.136
$mean(x_t)/10^6$	2.346	2.537	0.154	0.163	1.047	1.153	0.160	0.162	0.983	1.058
$var(y_t - y_{t-12})/10^9$	1.873	3.557	0.079	0.111	0.409	0.661	0.095	0.165	0.274	0.371
$var(y_t^1 - y_{t-12}^1)/10^9$	9.745	11.720	0.844	1.020	3.145	5.875	0.779	0.829	3.267	5.416
$var(y_t^2 - y_{t-12}^2)/10^9$	10.718	13.147	0.792	1.166	3.399	4.172	0.709	0.920	3.640	5.249
$var(y_t^3 - y_{t-12}^3)/10^9$	9.671	7.682	0.823	0.639	2.702	3.722	0.847	0.798	3.427	3.897
$var(y_t^4 - y_{t-12}^4)/10^9$	9.755	12.831	0.784	0.742	2.786	5.343	0.837	0.856	3.348	2.914
$var(y_t^5 - y_{t-12}^5)/10^9$	9.121	20.019	0.943	1.127	2.970	5.428	0.694	1.093	3.033	2.172
$var(y_t^6 - y_{t-12}^6)/10^9$	9.898	18.650	0.992	1.910	3.045	3.467	0.936	0.712	2.863	3.877
$var(y_t^7 - y_{t-12}^7)/10^9$	8.017	24.922	0.714	1.348	2.837	4.546	0.719	1.138	3.065	6.120
$var(y_t^8 - y_{t-12}^8)/10^9$	8.773	8.495	0.777	1.898	2.915	1.571	0.756	0.861	3.158	2.288
$var(x_t - x_{t-12})/10^9$	1.611	3.117	0.022	0.085	0.389	0.378	0.015	0.105	0.202	0.320
$\mathrm{corr}(y_t - y_{t-12}, x_t - x_{t-12})$	0.844	0.930	0.575	0.578	0.826	0.927	0.421	0.720	0.806	0.867

Note: x_t is the employment according to register.

Table 2 Descriptive statistics. Unemployed persons

	All domains/groups jointly		Males 15-24 years old		Males 25-74 years old		Females 15-24 years old		Females 25-74 years old	
	Until 2019	From 2020	Until 2019	From 2020	Until 2019	From 2020	Until 2019	From 2020	Until 2019	From 2020
$mean(y_t)/10^6$	0.097	0.133	0.020	0.025	0.036	0.049	0.015	0.022	0.027	0.037
$mean(y_t^1)/10^6$	0.112	0.152	0.022	0.026	0.041	0.060	0.016	0.024	0.032	0.043
$mean(y_t^2)/10^6$	0.102	0.132	0.020	0.024	0.038	0.047	0.016	0.021	0.028	0.040
$mean(y_t^3)/10^6$	0.095	0.146	0.020	0.032	0.036	0.049	0.014	0.023	0.025	0.042
$mean(y_t^4)/10^6$	0.095	0.127	0.020	0.024	0.035	0.047	0.015	0.018	0.025	0.037
$mean(y_t^5)/10^6$	0.094	0.132	0.020	0.025	0.034	0.045	0.015	0.023	0.025	0.038
$mean(y_t^6)/10^6$	0.090	0.122	0.019	0.023	0.033	0.049	0.014	0.020	0.025	0.030
$mean(y_t^7)/10^6$	0.093	0.125	0.018	0.023	0.035	0.047	0.015	0.023	0.025	0.032
$mean(y_t^8)/10^6$	0.097	0.131	0.018	0.022	0.037	0.050	0.015	0.022	0.027	0.037
$mean(x_t^A)/10^6$	0.067	0.120	0.006	0.009	0.033	0.059	0.004	0.007	0.024	0.046
$mean(x_t^B)/10^6$	0.066	0.087	0.006	0.007	0.031	0.042	0.004	0.005	0.024	0.033
$mean(x_t^C)/10^6$	0.066	0.087	0.006	0.007	0.031	0.042	0.004	0.005	0.024	0.033
$var(y_t - y_{t-12})/10^9$	0.281	1.159	0.028	0.028	0.090	0.307	0.022	0.042	0.044	0.149
$var(y_t^1 - y_{t-12}^1)/10^9$	1.368	2.373	0.205	0.198	0.589	0.983	0.208	0.224	0.492	0.683
$var(y_t^2 - y_{t-12}^2)/10^9$	1.682	2.113	0.228	0.201	0.677	0.495	0.220	0.272	0.366	1.018
$var(y_t^3 - y_{t-12}^3)/10^9$	1.399	3.587	0.239	0.213	0.526	0.708	0.161	0.285	0.261	0.763
$var(y_t^4 - y_{t-12}^4)/10^9$	1.409	2.347	0.227	0.194	0.508	0.690	0.162	0.192	0.272	0.404
$var(y_t^5 - y_{t-12}^5)/10^9$	1.180	2.745	0.215	0.190	0.458	0.899	0.135	0.253	0.330	0.451
$var(y_t^6 - y_{t-12}^6)/10^9$	1.209	2.074	0.164	0.187	0.455	1.171	0.145	0.198	0.269	0.174
$var(y_t^7 - y_{t-12}^7)/10^9$	1.268	2.390	0.163	0.281	0.529	0.665	0.156	0.230	0.261	0.341
$var(y_t^8 - y_{t-12}^8)/10^9$	1.411	2.474	0.174	0.139	0.512	0.805	0.186	0.380	0.352	0.638
$\mathrm{var}(x_t^A - x_{t-12}^A)/10^9$	0.117	9.810	0.002	0.059	0.042	2.190	0.000	0.077	0.009	1.304
$\mathrm{var}(x_t^B - x_{t-12}^B)/10^9$	0.095	0.978	0.002	0.009	0.031	0.210	0.000	0.009	0.008	0.127
$\mathrm{var}(x_t^C - x_{t-12}^C)/10^9$	0.096	0.882	0.002	0.008	0.031	0.191	0.000	0.007	0.009	0.115
$\mathrm{corr}(y_t - y_{t-12}, x_t^A - x_{t-12}^A)$	0.582	0.291	0.278	0.015	0.570	0.328	0.223	-0.116	0.333	0.355
$\mathrm{corr}(y_t - y_{t-12}, x_t^B - x_{t-12}^B)$	0.577	0.720	0.273	0.145	0.568	0.722	0.220	0.089	0.341	0.734
$\mathrm{corr}(y_t - y_{t-12}, x_t^C - x_{t-12}^C)$	0.562	0.804	0.254	0.226	0.558	0.773	0.213	0.115	0.340	0.830

Notes: x_t^A is the register series for unemployed persons from the Norwegian Labour and Welfare Administration (NAV), measured at the end of period t (typically the last Monday in the month): x_t^B is the register series for unemployed persons from NAV adjusted for temporary layoffs less than 90 days registered at NAV, i.e. $x_t^B = x_t^A - x_t^{layoffs}$ where $x_t^{layoffs}$ is the number of temporary layoffs less than 90 days according to NAV; x_t^C is the average of x_t^B near the beginning and end of the month, i.e. $x_t^C = (x_{t-1}^B + x_t^B)/2$.

2.2. The most important changes in the 2021-redesign of the Norwegian LFS

In the beginning of 2021, some changes were made in the Norwegian labour force survey. The main reason for the restructuring is new Eurostat requirements. The changes are intended to improve the quality of statistics, increase compatibility across countries, and improve comparability across domains in social statistics. Therefore, a similar restructuring of the LFS has taken place in all EU and associated countries. The sampling design was also changed in the Norwegian LFS, even though this was not a requirement from Eurostat. The sampling unit was changed from nuclear family to individual person.

The redesign also means that the target population was changed from covering all registered residents aged 15-74 to registered residents aged 15-89 in private households. This means that more age groups are included, but also that some persons are excluded from the target populations as they do not live in private households. The most important examples of the latter are persons enrolled in compulsory military service and persons registered as residents in institutions. 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 individual person, Statistics Norway has stopped using proxy interviewing. This change may have led to higher non-response, especially from younger people, but this should largely be compensated for by weighting. See Zhang et al. (2013) for a discussion of proxy interviewing in the Norwegian LFS.

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

From 2021 on, 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 the questionnaire, combined with the fact that the Norwegian labour market at the same time was facing a situation with many involuntarily laid-off in connection with the Covid-19 pandemic, reduces the number of unemployed when the new LFS design replaces the old one.

This paper is concerned with calculating the possible structural breaks caused by changes in the data collection process for persons aged 15-74 in connection with 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.

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

In the time series model for employed persons according to the LFS we utilize a time series for the number of registered employees in the domain.[4] Similarly, the time series model for LFS unemployment in a domain utilizes an auxiliary register time series for that domain from the unemployed registered at the employment office (registered unemployment). The auxiliary register variable in time series models needs to be comparable over time and should not include structural breaks, at least not at the same time as the 2021 redesign.

With respect to the LFS employment model, for the period before 2015, we use register information from the Employee Register. In January 2015, the Employee Register was replaced by the new A-Scheme register for monthly reporting of employee and payroll information to the Norwegian Labour and Welfare Administration (NAV), the Norwegian Tax Administration and Statistics Norway. From the time of the transition from the Employee Register to the new A-Scheme register, the auxiliary variable has been corrected for changed seasonal patterns and level changes. We also include a level shift at the time of the transition in our state-space model to capture possible level changes when estimating the model.

From Table 2 we see that there is a high correlation between LFS employment and registered employment. This correlation has been particularly high since 2020, with an estimated correlation coefficient of 93 percent for the full sample. The estimated correlation coefficients for the domains are somewhat lower but still exceeds 80 percent for the 'older' domains for both males and females. For young males, the correlation coefficient is estimated to be about 60 percent, and for young females, about 70 percent.

In the unemployment model, we use figures for persons registered by NAV as unemployed. Due to different treatment of temporary layoffs, there is a large discrepancy in the observed relationship between LFS unemployed and the official registered unemployed figures for the first couple of months of the Covid-19 pandemic in Norway, starting in March 2020. Therefore, "layoff-harmonized" registered unemployed figures have been constructed by excluding temporary layoffs in the first 3 months from the official NAV figures. This harmonization brings the definition more into line with the definition of LFS unemployment because the LFS treats temporary layoffs as employed temporarily

[4] We refer to variables which are not LFS variables as auxiliary variables.

absent for the first 90 days. This harmonization of the register variables is designed to bring about higher correlation between the register and LFS variables.

The official NAV unemployment figures indicate 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 the LFS, we use the average of the auxiliary register variables observed close to the end of the month in question and the end of the previous month. This averaging of our pre-adjusted harmonized register unemployment variable is vital in months with large changes in unemployment, such as for the initial shut-down period of the Covid-19 pandemic in Norway in March 2020.

Table 2 reveals the advantages of our adjustments of the registered unemployment series. When observations from January 2020 till October 2021 are considered for all domains together, the official NAV unemployment series shows a correlation of 29.1 percent with the LFS estimates. This correlation coefficient increases to 72.0 percent when we adjust for layoffs. When this adjusted register unemployment is measured as a two-month average, the correlation coefficient increases even further, to 80.4 percent. We see the same pattern for the domains we are considering, though the correlation coefficients are somewhat smaller. Due to our adjustments, the correlation coefficient for 'older' males increases from 32.8 to 77.3 percent. The estimate for 'older' females increases from 35.5 percent to 83.0 percent. For young males and females, the correlation between the register variables and the LFS variables is appreciably smaller. However, our adjustments increase the correlation for these domains, too.

2.4. Information from parallel data collection in 2020Q4

The results of a parallel data collection may help in a time series model to produce more precise estimates of the effect due to redesigning a survey. In the last quarter of 2020, a sample of 2,626 people was interviewed using the new questionnaire. The people in this extra sample were only interviewed once. The results of these interviews can be compared with the results from wave 1 of the ordinary LFS interviews when using the old questionnaire. This will give an estimate of the effect of the structural break for wave 1 together with a corresponding estimate of the variance.

The extra sample is too small for the effects of the 2021 redesign to be estimated precisely. However, the information can still be combined with a time series model to model the effects of the 2021 LFS redesign. This approach is discussed in van den Brakel et al. (2020).[5]

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

In Section 3.1, we outline the basic model for the Norwegian LFS. Section 3.2 presents our first contribution, which is the symmetric treatment of wave-specific effects. In Section 3.3, the model is extended to include a structural break and an auxiliary variable. The paper's second contribution is presented in Section 3.4, where we allow for a time-varying hyperparameter for the trends in order to estimate the effects of a structural break.

3.1. The basic state-space model of the Norwegian LFS

In this section, we reasonably assume that all the eight waves follow the same trend, have the same seasonal pattern and irregularities, and have an autocorrelated survey error component because of the rotating design. Pfeffermann (1991) derives a model for such a repeated survey.

We define y_t^i, where $i = 1,2,\ldots,8$, as the unemployment estimate (or the employment estimate) based on the observations in wave *i* of the LFS survey. Furthermore, let $Y_t = (y_t^1, y_t^2, \ldots, y_t^8)'$ be the vector of the estimates for all 8 waves. The model we use as a starting point is

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

where 1_8 is a column vector of 8 ones, θ_t is an estimate of the "true" LFS unemployment (or employment), the vector $\lambda_t = (\lambda_t^1, \lambda_t^2, \ldots, \lambda_t^8)'$ represents the time-varying wave-specific bias, and $e_t = (e_t^1, e_t^2, \ldots, e_t^8)'$ is the vector of wave-specific survey errors. Furthermore, the "true" LFS estimate is decomposed as

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

[5] Because the sample is small, a simplified version of the calibration model is used for deriving weights. A more detailed description of this model is given in Hamre et al. (2022).

where L_t is the level, S_t the seasonal, and I_t the irregular component. Below, we describe the processes for these three components and the wave-specific survey errors. The process for the wave-specific effects is presented in the next section.

The level is generally assumed to follow a local level model, a local linear trend model, or a smooth trend model; see e.g., Harvey (1989) and Durbin and Koopman (2012). We follow van den Brakel and Krieg (2009) and apply the smooth trend model

(5) $$L_t = L_{t-1} + R_{t-1}, \qquad R_t = R_{t-1} + w_t, \qquad w_t \sim N(0, \sigma_R^2)$$

The seasonal component, S_t, is often modelled as a deterministic seasonal model, a dummy seasonal model, or a trigonometric seasonal model; see among others Harvey (1989, pp. 41-43), Durbin and Koopman (2012), and Hindrayanto et al. (2013). With monthly data, the trigonometric seasonal model is given as[6]

(6) $$S_t = \sum_{j=1}^{6} \gamma_{j,t}$$
$$\gamma_{j,t} = \gamma_{j,t-1} \, cos(\pi j/6) + \gamma_{j,t-1}^{*} \, sin(\pi j/6) + \omega_{j,t} \;\; \omega_{j,t} \sim N(0, \sigma_\omega^2)$$
$$\gamma_{j,t}^{*} = \gamma_{j,t-1}^{*} \, cos(\pi j/6) - \gamma_{j,t-1} \, sin(\pi j/6) + \omega_{j,t}^{*} \;\; \omega_{j,t}^{*} \sim N(0, \sigma_\omega^2) \qquad j = 1,2, \dots ,6.$$

The first frequency of $\pi/6$, i.e., the fundamental frequency, corresponds to a period of 12 months, whereas the five other frequencies are harmonics. We note that this process depends here on only one parameter, as the variance σ_ω^2 is common to all disturbance terms. This is a restriction commonly used for these hyperparameters; see e.g., Harvey (1989).

The irregular component I_t is assumed to be white noise, independently and identically distributed:

(7) $$I_t \sim \mathrm{N}(0, \sigma_I^2).$$

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 of the wave-specific survey errors is also

[6] Note that $cos(\pi) = -1$ and $sin(\pi) = 0$. Therefore, for $j = 6$ we have $\gamma_{6,t} = -\gamma_{6,t-1} + \omega_{6,t}$ and the process for $\gamma_{6,t}^{*}$ is redundant.

time-dependent, partly due to variation in the number of people interviewed each month. Let $k_t^j = \sqrt{\widehat{Var}[y_t^j]}$ be an estimate of the standard error of the survey error. The survey errors are modelled as:

(8) $$e_t^j = k_t^j \, \tilde{e}_t^j \text{ where } \tilde{e}_t^1 = \varepsilon_t^1 \text{ with } \varepsilon_t^1 \sim N(0, \sigma_{e_1}^2)$$
$$\text{and } \tilde{e}_t^j = \phi \, \tilde{e}_{t-3}^{j-1} + \varepsilon_t^j \text{ with } \varepsilon_t^j \sim N(0, \sigma_e^2) \text{ for } j = 2,3,\dots,8$$

If k_t^j is a 'good' estimate of the standard error of the survey error, $\tilde{e}_t^j$ will have an estimated variance of close to one. We do not impose such a restriction here. However, we impose that $Var(\tilde{e}_t^2) = \cdots = Var(\tilde{e}_t^8)$, from which it follows that $\sigma_{e_2}^2 = \sigma_{e_3}^2 = \cdots = \sigma_{e_8}^2$, which are restrictions we impose on the system.[7]

A rough approximate estimate of the variance of the wave-specific monthly LFS-estimates is

(9) $$\widehat{Var}[y_t^j] = N_t^2 \hat{p}_t (1 - \hat{p}_t)/n_t^j,$$

where n^j is the net LFS sample size in wave j, N_t is the population size; and $\hat{p}_t = \left(\frac{1}{8}\sum_{j=1}^{8} y_t^j\right)/N_t$ is the estimated proportion for an LFS variable based on information from all 8 waves.

The autocorrelation coefficient in (8), ϕ, is estimated in a system with a panel of pseudo errors, which was also the starting point of Pfeffermann et al. (1998). However, instead of applying the approach in Pfeffermann et al. (1998), we estimate the autocorrelation coefficient of the survey errors directly by treating the system as a vector autoregressive system with cross-equation restrictions. The procedure for estimating the autocorrelation coefficient is outlined in Appendix A. The estimate obtained is plugged into our state-space model when the remaining parameters are estimated.

3.2. Symmetric treatment of the wave-specific effects

Investigating the responses from the US current population survey (which corresponds to the LFS in many other countries), Bailar (1975) shows that the number of people reporting as unemployed is much higher for those participating in the survey for the first time. Similar results for the US current

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[7] By imposing the restrictions $Var(\tilde{e}_t^1) = \cdots = Var(\tilde{e}_t^8)$, i.e. by also including the variance for the first wave, it also follows that $\sigma_{e_1}^2 = \sigma_e^2/(1 - \phi^2)$, 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 take account of the fact that our estimate of ϕ might be biased, we do not impose this restriction.

population survey are also found in Stephan et al. (1954, p. A-80) and Hansen et al. (1955, p. 710), and in Kumar et al. (1983) for the Canadian LFS. Pfeffermann (1991) takes account of this in his model for repeated surveys by including wave-specific effects. However, the model only takes account of time-invariant wave-specific effects (although he mentions that the model can be extended to allow for time-varying wave-specific effects). van den Brakel and Krieg (2009) extend the model to include time-varying wave-specific effects. Bailar (1975) and Krueger et al. (2017) show that the time-varying wave-specific effects are not time-invariant.

For both the level component in θ_t and the wave-specific effects to be identifiable, a restriction must be imposed on the wave-specific effects. van den Brakel and Krieg (2009) assume that the estimate of the unemployment rate from the first wave is unbiased. Thus, they apply the restriction $\lambda_t^1 = 0$.
In contrast, we apply the restriction $1_8'\lambda_t = 0$, i.e., the sum of the wave-specific effects is zero in every period. It is usually imposed by restricting one of the components in λ_t, for example, the last one, to being equal to the negative sum of the others, and allowing the remaining ones to follow independent random walks (see, e.g., Elliot and Zong, 2019). However, this will often lead to a large variance in the wave-specific bias for the wave that ensures that the restriction holds. For example, if we have $\lambda_t^j = \lambda_{t-1}^j + \eta_t^j$ with $\eta_t^j \sim \text{iid}N(0, \sigma_\lambda^2)$ for $j = 1,2, \dots ,7$, and $\lambda_t^8 = -\sum_{j=1}^{7} \lambda_t^j$, then $Var(\lambda_t^j - \lambda_{t-1}^j) = \sigma_\lambda^2$ for $j = 1,2, \dots ,7$ but $Var(\lambda_t^8 - \lambda_{t-1}^8) = 7\sigma_\lambda^2$.

To avoid the process of one of the wave-specific effects having a higher variance than the other, we apply a symmetric approach;

$$(10) \qquad \lambda_t = \lambda_{t-1} + \eta_t \qquad \eta_t \sim N\left(0_8,\ \left(I_8 - \tfrac{1}{8} 1_8 1_8'\right) \sigma_\lambda^2\right), \quad 1_8'\lambda_0 = 0$$

where I_8 is the identity matrix of dimension 8. Note that η_t has a singular covariance matrix. The formulation in (10) ensures that $1_8'\lambda_t = 0$. The representation in (10) is similar to the representation for seasonal effects in Harrison and Stevens (1976); see also Proietti (2000) and Harvey (2006). Proietti (2000) discusses the similarity between the trigonometric seasonal model in (5) and a seasonal model in the form of (10).

The formulation of the wave-specific effects in (10) might not be easy to implement in a software program for state-space models. The restriction $1_8'\lambda_t = 0$ implies that there are 7 independent variables in λ_t. Therefore, we introduce the 7 times 8 matrix J^* and the 7-dimensional vector λ_t^* of the

7 independent variables in λ_t, such that we have $\lambda_t = J^* \lambda_t^*$. The process of these 7 independent variables can be formulated as 7 independent random walks;

(11) $$\lambda_t^* = \lambda_{t-1}^* + \eta_t^*, \quad \eta_t^* \sim N(0_7, I_7\, \sigma_\lambda^2).$$

Note that if we premultiply (11) with J^*, we get (10) if $J^* J^{*\prime} = I_8 - \frac{1}{8} 1_8 1_8'$. This will be the case if we choose $J^* = J(J'J)^{-1/2}$ with $J' = (I_7, -1_7)$.[8]

3.3. Structural break and auxiliary variables

We now extend our model to allow for a possible structural break following Harvey and Durbin (1986). When a structural break is included, (3) changes to

(12) $$Y_t = 1_8 \theta_t + \lambda_t + \beta 1_{t \geq 2021M1} + e_t.$$

In (12), $1_{t \geq 2021M1}$, is a dummy variable that changes from zero to one when the survey changes from the old to the new design in January 2021. The 8-dimensional vector with regression coefficients, $\beta = (\beta^1, \beta^2, \dots, \beta^8)'$ represents the effect of the structural break for each wave.[9]

We include auxiliary variables in the models to improve the discontinuity estimates. If X_t is such a variable (e.g., unemployment information from a register, or employment information from a register):

(13) $$X_t = \theta_t^X = L_t^X + S_t^X + I_t^X,$$

where L_t^X, S_t^X, I_t^X are scalars and denote the level, seasonal, and irregular components of the auxiliary variable. They are modelled similarly to the corresponding components of the LFS variables in (5)-(7). van den Brakel and Krieg (2015) suggest constructing a model in which the vector Y_t and the scalar X_t are modelled jointly. This joint system can be formulated as

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[8] Note that $S = J'J$ is both symmetric and positive definite. A symmetric matrix can be decomposed using eigen-decomposition as $S = V \Lambda V'$, where Λ is a diagonal matrix holding the eigenvalues and V a matrix with the corresponding eigenvectors. As S is also positive definite, we have $S^n = V \Lambda^n V'$ when n is any real number. Here we apply this for $n = -1/2$.

[9] In the estimation we also include a break in 2015M1. This break accounts for a possible level shift due to a less informative auxiliary register variable before 2015 being applied in the LFS weighting procedure. In 2015, Norway got the new high-quality A-Scheme register, which is a register of pay slips submitted to the tax authorities. Up until 2014 Norway had the Aa-register of change notifications (with delays) regarding employers' hiring and firing which were submitted to NAV.

(14) $$\begin{pmatrix} Y_t \\ X_t \end{pmatrix} = \begin{pmatrix} 1_8 \theta_t^{LFS} \\ \theta_t^X \end{pmatrix} + \begin{pmatrix} \lambda_t \\ 0 \end{pmatrix} + \begin{pmatrix} \beta \\ 0 \end{pmatrix} 1_{t \geq 2021M1} + \begin{pmatrix} e_t \\ 0 \end{pmatrix}.$$

For it to be advantageous to model the LFS variable (LFS unemployment or LFS employment) and the register variable jointly, there must be a correlation between them. When a smooth trend model is applied, the most important component in θ_t is the slope component. Therefore, we allow the slope components of the LFS variables and the auxiliary variable, the X-variable, to be correlated. The covariance between the slopes of LFS variable trend and the register variable trend is given by

(15) $$\mathrm{Cov}(w_t^{LFS}, w_t^X) = \rho_R^{LFS,X} \sigma_R^{LFS} \sigma_R^X,$$

where σ_R^{LFS} is the square root of σ_R^2 in (5), which is the slope variance of the LFS variable trend, σ_R^X is the square root of the slope variance of the register variable trend, and $\rho_R^{LFS,X}$ is the correlation between the two slope disturbances.

3.4. 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 large fluctuations in the labour market. The structural break estimates may be severely biased if this increased variation in the LFS and register time series is neglected.

In the Netherlands, the Labour Force Survey estimates are improved by applying a state-space model; see van den Brakel and Krieg (2009). During the Covid-19 pandemic, they had to modify the state-space model to account for the more rapid changes in the labour market; see van den Brakel et al. (2022). They did so by allowing for a time-varying hyperparameter for the slope. Here, we use similar modelling of both the LFS and the register trend.

(16) $$L_t^i = L_{t-1}^i + R_{t-1}^i, \qquad R_t^i = R_{t-1}^i + \psi_t^{1/2} w_t^i, \qquad w_t^i \sim \mathrm{N}\left(0, (\sigma_R^i)^2\right), \quad i = LFS, X$$

The formulation in (16) implies that the hyperparameter for the slope-variance is time-varying and given by $\psi_t \left(\sigma_R^i\right)^2$.

We have divided our sample into three parts. The first 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 of the slope in the pre-corona period. The second 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. For this period we restrict ψ_t to take the same value in all months, i.e. $\psi_t = \psi 1$ for $t = 2020M1, 2020M2, \dots, 2020M6$. The last part, the recovery period, starts in mid-2020. In this period, there were still larger fluctuations than before the coronavirus (Covid-19) crises, but not as large as when the pandemic first hit the Norwegian economy. For this period, which applies to the remainder of our sample, we also restrict ψ_t to taking the same value in all months, i.e. $\psi_t = \psi 2$ for $t = 2020M7, 2020M8, \dots, 2021M10$.

3.5. Estimation and statistical inference

We cast our (parsimonious) models in state-space form and estimate their hyperparameters by maximizing the diffuse loglikelihood function using the BFGS algorithm. The formal specification of the state-space model with all the underlying assumptions is given in Appendix B. Special features of our state-space models are that there are no measurement errors in the measurement (vector) equation, the transition matrices are always time-invariant, and the selection matrices of the transition equations are potentially time-varying. The main purpose of our paper is to investigate whether the redesign of the LFS survey impacts employment and unemployment. The intervention effects are assumed to be wave-specific and constant. Technically, they are represented by elements in the state vector that are without disturbances. Thus, after the intervention has taken place, there is no evolution of the intervention effects over time.

The target function is given in Helske (2017, Section 2.1). As in the non-diffuse case, the innovations are utilized, i.e., the one-step-ahead prediction errors, an idea that goes back to Schweppe (1965). An essential part of the estimation algorithm is to run the Kalman filter during the recursions in order to update the state vector estimate. KFAS utilizes a complete univariate approach for filtering and smoothing provided by Koopman and Durbin (2003); see also Anderson and Moore (1979) for sequential processing. This constitutes a way of implementing so-called exact diffuse initialization. Such a procedure makes the results less prone to numerical error than when uninformative diffuse priors are used. In Appendix B, we provide the state-space form representation of the model we apply. An important aspect of our study is to compare model specifications with time-invariant hyperparameters with model specifications that allow for time-varying hyperparameters. To this end, we use likelihood ratio tests.

After obtaining the maximum likelihood estimates of our unknown hyperparameters, we obtain (final) smoothed estimates of the state vectors. Diagnostics related to the behaviour of the disturbances in the state vector can be derived from the smoothed estimates of the state vector. For instance, we calculate auxiliary residuals corresponding to the disturbances in the slope component of the trend. They can be used to assess the suitability of the model.

4. Results

This section presents the estimated hyperparameters, other model results, and the structural break estimates due to the 2021 LFS-redesign. The models are estimated on monthly data from 2006M1 to 2021M10. The structural break estimates are allowed to vary across the four domains we consider. Apart from the pre-estimation of the autocorrelation parameters related to the survey error component, all other inference has been carried out using the R package KFAS, see Helske (2017).[10]

Following Pfeffermann et al. (1998), we estimate the autocorrelation coefficient of the survey errors in a separate system; see Appendix A. By doing so, we can treat the coefficient as "known" when estimating the remaining parameters of the state-space model.

We apply a grid search technique to estimate $\psi 1$ and $\psi 2$. We construct a two-dimensional grid for $\psi 1$ and $\psi 2$ (where $1 \leq \psi 1 \leq \psi 2$). For each pair of values for $\psi 1$ and $\psi 2$, we estimate the remaining parameters of the state-space model and calculate the log-likelihood value. The estimates of $\psi 1$ and $\psi 2$ are given by the pair of values that lead to the highest log-likelihood value.[11]

4.1. Estimated hyperparameters and other results

Table 3 provides an overview of the maximum likelihood estimates of the hyperparameters for employment. In the table, we consider both the case with estimated parameters $\psi 1$ and $\psi 2$ and the case where the parameters are fixed a priori at 1. The former specification allows the variance of the disturbances of the slope component of the trend to be time-varying.

The estimates of $\psi 1$ and $\psi 2$ are quite large. The estimate of $\psi 1$ for the different domains ranges from 16 to 49. This implies that the variance of the disturbances related to the slope of the trend component

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

[11] After trying out a couple of different versions of the grid, we ended up using the following crude grid values in our search: $\psi 1 = 16,25,49$ and $\psi 2 = (\psi 1 + \psi_{step} - 1)$, where $\psi_{step} = 2,4,6,8,12,24,48$. See also Appendix C.

is 16 to 49 times as high during the first part of the Covid-19 pandemic, as in the pre-pandemic period. The estimates of $\psi2$ are smaller, as they cover the second part of the Covid-19 pandemic. The estimates range from about 3 to 13 across the different domains.

Table 3 also reveals a high correlation between the disturbances of the slopes of the LFS- and register trends. For all domains, the estimated correlation between the disturbances of the two trend-slopes is equal or almost equal to 1. This strong correlation is advantageous for estimating possible structural breaks due to the 2021 LFS-redesign. A correlation equal to 1 implies that the LFS-variable and the register variable have a common stochastic trend and thus cointegrate; see Engle and Granger (1987). Due to normally more stable labour market status over time for persons aged 25-74 than for persons aged 15-24, we see from Table 3 that the estimated autocorrelation in the survey errors, $\widehat{\phi}$, is higher for the oldest age group for both males and females.

We have also tested the joint hypothesis of time-invariant hyperparameters, i.e., $\psi1 = \psi2 = 1$, using a likelihood ratio test. It is clearly rejected for all domains. All the p-values are less than 0.0001.

Auxiliary residuals are smoothed estimates of the disturbances associated with the unobserved components. Harvey and Koopman (1992) show that the auxiliary residuals are useful for detecting outliers and structural changes. We concentrate on graphs displaying auxiliary residuals related to the slope component of the trend. Figures C.1 and C.2 in Appendix C illustrate the importance of allowing for a time-varying variance for the slope of the trend when modelling employment. Figure C.1 shows the above-mentioned auxiliary residuals when we allow for time-varying variance for the four domains. Figure C.2 shows the auxiliary residuals when we do not allow for time-varying variances of the slope disturbances. In the latter figure, we see that the volatility of the residuals is much higher in 2020 and 2021 than in previous years. However, when allowance is made for stepwise time-varying variances for the two slope components (Figure C.1), the residuals seem to perform better than in the time-invariant case. We interpret this as evidence that our formulation of the stepwise shifts in the variances of the disturbances of the slope components of the trends captures quite well the excess employment fluctuations in the last part of the sample that are present in the case with time-invariant hyperparameters.

Table 3 Estimated hyperparameters. Employed persons

Hyperparameters	With allowance for time-varying variances for the disturbances of the slope components				With allowance for time-varying variances for the disturbances of the slope components			
	Male 15-24	Male 25-74	Female 15-24	Female 25-74	Male 15-24	Male 25-74	Female 15-24	Female 25-74
ψ_1	25	16	25	49	1	1	1	1
ψ_2	13	2.875	13	13	1	1	1	1
$(\sigma_R^{LFS})^2/10^6$	0.017	0.291	0.023	0.033	0.306	1.500	0.294	1.969
$(\sigma_\omega^{LFS})^2/10^3$	15.225	12.694	5.549	0.011	16.223	12.245	3.749	0.000
$(\sigma_I^{LFS})^2/10^6$	1.218	0.000	4.532	1.380	1.405	0.000	4.595	0.318
$(\sigma_\lambda^{LFS})^2$	1.033	2.846	9.269	42.109	138.436	0.000	32.223	0.000
$(\sigma_\varepsilon^1)^2$	1.150	1.181	1.058	1.314	1.151	1.177	1.048	1.309
$(\sigma_\varepsilon^2)^2 = (\sigma_\varepsilon^3)^2 =\ldots= (\sigma_\varepsilon^8)^2$	0.713	0.538	0.694	0.455	0.713	0.541	0.689	0.455
$(\sigma_R^X)^2/10^6$	0.023	0.453	0.036	0.047	0.441	2.666	0.680	2.495
$(\sigma_\omega^X)^2/10^3$	5.531	0.013	4.465	2.958	5.104	0.023	5.869	0.000
$(\sigma_I^X)^2/10^6$	0.211	0.730	0.062	0.365	0.264	0.701	0.018	0.453
$\rho_R^{LFS,X}$	1.000	0.999	1.000	1.000	1.000	1.000	0.986	1.000
ϕ	0.577	0.723	0.539	0.770	0.577	0.723	0.539	0.770

Table 4 Estimated hyperparameters. Unemployed persons

Hyper-parameters	With allowance for time-varying variances for the disturbances of the slope components				With allowance for time-varying variances for the disturbances of the slope components			
	Male 15-24	Male 25-74	Female 15-24	Female 25-74	Male 15-24	Male 25-74	Female 15-24	Female 25-74
ψ_1	16	16	49	25	1	1	1	1
ψ_2	1.3125	2.25	5	4	1	1	1	1
$(\sigma_R^{LFS})^2/10^6$	0.004	0.105	0.001	0.036	0.033	0.411	0.000	0.355
$(\sigma_\omega^{LFS})^2/10^3$	1.059	0.059	1.252	6.053	0.935	0.024	3.097	5.281
$(\sigma_I^{LFS})^2/10^6$	0.000	0.000	2.380	0.000	0.006	0.016	2.786	0.001
$(\sigma_\lambda^{LFS})^2$	0.000	14.698	0.069	6.013	0.122	68.734	385.470	36.661
$(\sigma_\varepsilon^1)^2$	1.224	1.579	1.309	1.830	1.221	1.585	1.317	1.836
$(\sigma_\varepsilon^2)^2 = (\sigma_\varepsilon^3)^2 =\ldots= (\sigma_\varepsilon^8)^2$	1.148	1.350	1.142	1.118	1.147	1.342	1.145	1.115
$(\sigma_R^X)^2/10^6$	0.007	0.158	0.002	0.046	0.048	0.560	0.156	0.421
$(\sigma_\omega^X)^2/10^3$	0.003	0.003	0.000	0.006	0.024	0.316	0.007	0.203
$(\sigma_I^X)^2/10^6$	0.000	0.000	0.000	0.000	0.001	0.374	0.000	0.232
$\rho_R^{LFS,X}$	0.991	1.000	0.999	1.000	0.998	1.000	0.957	1.000
ϕ	0.106	0.259	0.081	0.267	0.106	0.259	0.081	0.267

Table 4 provides maximum likelihood estimates of the hyperparameters in the unemployment models. As for employment, we consider both the case where we allow for a time-varying variance for the disturbances of the slopes of the trend components and the case where we do not. When allowing for time-varying variances, we get estimates of $\psi 1$ ranging from 16 to 49. The estimates of $\psi 2$ range from about 1.3 to 5. Thus, the estimates of $\psi 2$ are somewhat smaller for unemployment than for employment (in Table 3).

As we did for employment, we formally test the joint hypothesis of time-invariant, i.e., $\psi 1 = \psi 2 = 1$ against the alternative of time-varying hyperparameters using a likelihood ratio test. The hypothesis is firmly rejected for all domains. Again, all p-values are less than 0.0001. This finding is not surprising when Figures C.3 and C.4 are compared. In these graphs, the auxiliary residuals of the slope components of the trends are shown for both the case where we allow for time-varying variances for the slopes of the two trend components (Figure C.3) and for the case where we assume that they are time-invariant (Figure C.4). As in the case of employment (in Figure C.2), we see clearly that the variance increases in 2020 and 2021 in Figure C.4. When we allow for stepwise shifts in the variances of the disturbances of the two slopes, Figure C.3 does not show any evident structural breaks in the volatility of the residuals. Therefore, as in the the case for employment, we interpret this as evidence that our formulation of the stepwise shifts in the variances of disturbances of the two slope components captures the time-invariance caused by the pandemic quite well.

4.2. Level shift parameter estimates

Table 5 reports the structural break estimates for employment in the four domains both when we allow for time-varying hyperparameters and when we do not. The estimated total effect of the structural break in employment is 21,864 persons when we allow for time-varying hyperparameters and 24,307 when we do not. Measured relative to an LFS-population of 4 million, the estimated structural break represents about 0,6 percent of the LFS-population. From the table, we see that it is the structural break estimate for males aged 25-74 that is most affected by allowing for a time-varying hyperparameter: When assuming time-invariant hyperparameters, we obtain a structural break estimate for this domain of 5,002 persons, but this estimate changes to -381 when allowance is made for time-varying hyperparameters for the slopes. The structural break estimate for young females also changes when allowance is made for time-varying hyperparameters, from 5,442 to 8,115.

When time-varying variances for the slopes are allowed for, the structural break estimates for males are small and insignificant, when measured either individually or jointly. The estimates for women are all positive and significant. Thus, our analysis implies that the redesign of the Norwegian LFS led to an increase in measured employment for women.

Table 6 reports estimates of the effects of the structural break for unemployment in the four domains. When time-varying hyperparameters for the two slope parameters are allowed for, the total estimated effect of the structural break on unemployment figures is 5,371. This corresponds to just over 0.1 percent of the LFS-population. When the hyperparameters of the two slopes are assumed to be time-invariant for all domains, the estimated total effect of the structural break is 7,841 persons, or about 0.2 percent of the LFS population. The estimates for unemployed females are virtually unaltered by allowing for time-varying hyperparameters. Therefore, the change in the total structural break estimate when allowance is made for time-varying slope hyperparameters of the slopes is due to the change in the estimates for males. The overall structural break estimate for males is reduced by more than 2,000 people (from 3,847 to 1,723) when time-varying variances are allowed for the slope parameters.

Table 5 Structural break estimates for employed persons, by sex and age[a]

Sex and age	Optimal time-varying hyperparameters		Time-invariant hyperparameters	
	Parameter estimate	Standard error	Parameter estimate	Standard error
Males aged 15-24	-1,608	2,252	-1,925	2,249
Males aged 25-74	-381	4,025	5,002	3,697
Females aged 15-24	8,115	2,145	5,442	2,389
Females aged 25-74	15,738	3,709	15,788	3,566
Total: aggregate of the 4 domains	21,864	6,295	24,307	6,095
Total for those aged 15-24: aggregate of the 2 sex groups	6,507	3,110	324	5,943
Total for those aged 25-74: aggregate of the 2 sex groups	15,357	5,473	20,790	5,137
Total for males: aggregate of the two age groups	-1,989	4,612	3,077	4,327
Total for females: aggregate of the two age groups	23,853	4,285	21,230	4,292

[a] The period of the analysis is 2006M1-2021M10. The uncertainties for the 2021-redesign level shift parameter estimates measured with the standard error reported are based on the case that $\psi 1$, $\psi 2$, and ϕ are known.

Table 6 Structural break estimates for unemployed persons, by sex and age[a]

Sex and age	Optimal time-varying hyper-parameters		Time-invariant hyper-parameters	
	Parameter estimate	Standard error	Parameter estimate	Standard error
Males aged 15-24	3,275	1,670	4,799	1,475
Males aged 25-74	-1,552	2,346	-952	2,198
Females aged 15-24	4,940	1,442	5,163	1,342
Females aged 25-74	-1,292	1,736	- 1,169	1,739
Total: aggregate of the 4 domains	5,371	3,659	7,841	3,440
Total for those aged 15-24: aggregate of the 2 sex groups	8,215	2,206	9,962	1,994
Total for those aged 25-74: aggregate of the 2 sex groups	-2,844	2,918	-2,121	2,803
Total for males: aggregate of the two age groups	1,723	2,880	3,847	2, 647
Total for females: aggregate of the two age groups	3,648	2,257	3,994	2,197

[a]The period of analysis is 2006M1-2021M10. The uncertainties for the 2021-redesign level shift parameter estimates measured with the standard error reported are based on the case that $\psi 1$, $\psi 2$, and ϕ are known.

5. Conclusions

In 2021, the Norwegian LFS underwent a substantial redesign in accordance with the new regulation for integrated European social statistics. To ensure coherent labour market time series for the main indicators, the redesign's impact is modelled to enable back-calculated estimates to be adjusted for possible structural breaks due to the 2021 LFS redesign.

We pursued a structural time series approach in the tradition of Pfeffermann (1991), van den Brakel et al. (2009, 2015) and Elliott and Zong (2019). Structural breaks were estimated for the numbers of employed and unemployed persons in different domains.

In addition to the 8 waves of monthly LFS data for the numbers of employed and unemployed persons, we also included auxiliary time series for registered numbers of employed and unemployed, in the model specifications.

The structural time series model used 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 take account of wave-specific effects and the autocorrelation structure of the survey error component brought about by the rotating panel design.

The auxiliary time series were also decomposed into trend, seasonality and irregularity components. Information from the auxiliary variables was used to obtain more precise structural break estimates by allowing the disturbances of the slopes of the two trend components to be correlated.
The large labour market fluctuations due to the Covid-19 pandemic affected the structural break estimates following the redesign of the LFS. To counteract this contamination, we allowed the trend hyperparameters to be higher during the pandemic.

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

We considered models for four main domains: females aged 15-24, females aged 25-75, males aged 15-24 and males aged 25-75. The domain-specific structural break estimates are given as the average of the estimates of the structural break parameters for the 8 waves.

We obtained a positive structural break estimate of about 22,000 employed and 5,000 unemployed persons aged 15-74 when allowing for a time-varying hyperparameter for the slopes of the two trend variables. When no such allowance was made, the estimated breaks for employment and unemployment were about 2,000-3,000 higher. Both likelihood ratio tests and examination of the auxiliary residuals indicate that the hyperparameters for slopes are time-varying with higher variances during the Covid19 pandemic.

The structural break estimates identified here for Norway are of the same sign as found in the Netherlands; see van den Brakel (2022). However, our estimates are much smaller. van den Brakel (2022) identifies a structural break estimate in employment that corresponds to more than 1.5 percent of the population in the LFS, and a structural break estimate in unemployment that exceeds 1 percent of the LFS-population. For Norway, the estimates of the structural break imply a positive shift in the employment figure of slightly less than 0.6 percent and for unemployment of just over 0.1 percent, measured in relation to the LFS population.

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Appendix A: Survey errors

Because of the survey design, which implies that the respondents are asked questions 8 times over 2 years, i.e. each quarter for two years, the derived time series will be subject to autocorrelation. Neglecting the survey error component will cause 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 the remaining parameters are estimated.

Construction of pseudo errors

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

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

and

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

Model specification

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

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

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

Each of the two systems is characterized by only one parameter in the systematic part, i.e. 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. We define the following vectors with errors.

(A.5) $\xi_{u,t} = [\xi_{u,t}^2, \quad \xi_{u,t}^3, \quad \xi_{u,t}^4, \quad \xi_{u,t}^5, \quad \xi_{u,t}^6, \quad \xi_{u,t}^7, \quad \xi_{u,t}^8]^{/}$

and

(A.6) $\xi_{e,t} = [\xi_{e,t}^2, \quad \xi_{e,t}^3, \quad \xi_{e,t}^4, \quad \xi_{e,t}^5, \quad \xi_{e,t}^6, \quad \xi_{e,t}^7, \quad \xi_{e,t}^8]^{/}.$

We assume that

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

and

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

where both $\Omega_u$and Ω_e are full covariance matrices. The two models are estimated by the SURE procedure in the r-package Systemfit; see Henningsen and Hamann (2007).[12] In Table A1, 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

Robustness

In our modelling, we have placed emphasis on employing a parsimonious model. The approach can be extended in different directions. One involves operating with wave-specific autocorrelation parameters. Unreported results show that the above implicit homogeneity assumptions are rather innocent. Another extension involves extending 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

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

we model the pseudo-errors for employed and unemployed simultaneously. Under this more general model, we can for instance specify that $\varepsilon_{u,t-3}^{j-1}$ influences $\varepsilon_{e,t}^{j}$. However, although 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 $\Omega_u$and Ω_e, but the results seemed fairly robust with respect to this type of change of the specification.

Appendix B: The state-space model in detail

We specify the model in state-space form. To derive the explicit state-space form of the system, we apply some new symbols for different operations. Let *Diag* create a diagonal matrix from the elements in parentheses, and *BlockDiag* create a block diagonal matrix from the elements in the parentheses. Let $\otimes$ express the Kronecker product. The measurement vector equation is given as

(B.1) $$y_t = Z_t \alpha_t,$$

where $\boldsymbol{y}_t = (y_t^1, y_t^2, \ldots, y_t^8, X_t)'$ is a vector of all 8 waves of the LFS variable plus an auxiliary variable, where the state vector $\boldsymbol{\alpha_t}$ is a vector of unobserved components for level (R and L), season (γ and γ^*), irregular component (I), wave-specific effects (the λ's), and 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 of the auxiliary variable. Finally, the structural break parameters for all LFS waves are included in α_t. Hence, the full state vector can be written in the following partitioned form

(B.2) $$\alpha_t = \left(\alpha_t^{L'}, \alpha_t^{S'}, \alpha_t^{I'}, \alpha_t^{e'}, \alpha_t^{\lambda'}, \alpha_t^{b'}\right)'.$$

The vector $\alpha_t^{L'}$ consists of four elements. The first two are the level and slope of the LFS waves, the last two are the level and slope of the auxiliary variable. Further, the vector $\alpha_t^{S'}$ consists of 24 elements. The first 12 relate to the seasonality of the LFS waves, and the last 12 to the seasonality of the auxiliary variable. (However, since $\sin\pi = 0$, we can exclude columns 12 and 24 from Z_t^S, and both rows and columns 12 and 24 from the remaining matrices). The vector $\alpha_t^{I'}$ consists of 2 elements, where the first is the irregular component of the LFS waves and the last is the irregular component of the auxiliary variable. The vector $\alpha_t^{e'}$ consists of 24 elements, all related to the LFS waves. The first 8 are the survey errors for the 8 waves, the next 8 are the survey errors lagged one period, and the last 8 are the survey errors lagged 2 periods. (However, we can exclude columns 12 and 24 from Z_t^e, and both rows and columns 12 and 24 from the remaining matrices). The vector $\alpha_t^{\lambda'}$ consists of 7 components for the wave-specific biases. Finally, the vector $\alpha_t^{b'}$ consists of 8 components with the effects of the structural break in each of the 8 waves.

The matrix $\boldsymbol{Z_t}$ contains only known values, 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-varying, as it includes values of the structural break variable $1_{t\geq 2021M1}$. It may be partitioned as

(B.3) $$Z_t = \left(Z_t^L, Z_t^S, Z_t^I, Z_t^e, Z_t^\lambda, Z_t^b\right),$$

where

(B.4) $$Z_t^L = \begin{pmatrix} 1_8(1 \quad 0) & 0_8 0_2' \\ 0_2' & (1 \quad 0) \end{pmatrix},$$

(B.5) $$Z_t^S = \begin{pmatrix} 1_6' \otimes (1,0) 1_8 & 0_8 0_{12}' \\ 0_{12}' & 1_6' \otimes (1,0) \end{pmatrix},$$

(B.6) $$Z_t^I = \begin{pmatrix} 1_8 & 0_8 \\ 0 & 1 \end{pmatrix},$$

(B.7) $$Z_t^e = \begin{pmatrix} Diag\left(k_t^1, k_t^2, k_t^3, k_t^4, k_t^5, k_t^6, k_t^7, k_t^8\right) & 0_8 0_{16}' \\ 0_8' & 0_{16}' \end{pmatrix},$$

(B.8) $$Z_t^\lambda = \begin{pmatrix} J^* \\ 0_7' \end{pmatrix}$$

and

(B.9) $$Z_t^b = \begin{pmatrix} 1_{t\geq 2021M1} I_8 \\ 0_8' \end{pmatrix}.$$

The transition equation is given by

(B.10) $$\alpha_{t+1} = T\alpha_t + G_t \nu_t, \text{ with } \nu_t \sim N(0, Q),$$

where the time-invariant transition matrix T contains mostly 0 and 1, but also the estimate of the autocorrelation parameter ϕ related to the survey error component. It has the following block-diagonal specification

(B.11) $$T_t = BlockDiag\left(T_t^L, T_t^S, T_t^I, T_t^e, T_t^\lambda, T_t^b\right),$$

where

(B.12) $$T_t^L = \begin{pmatrix} 1 & 1 \\ 0 & 1 \end{pmatrix} \otimes I_2,$$

(B.13) $$T_t^S = \left(BlockDiag\left(T_t^{S_1}, T_t^{S_2}, T_t^{S_3}, T_t^{S_4}, T_t^{S_5}, T_t^{S_6}\right)\right) \otimes I_2 ,$$

with $T_t^{S_j} = \begin{pmatrix} cos(\pi j/6) & sin(\pi j/6) \\ -sin(\pi j/6) & cos(\pi j/6) \end{pmatrix}$ for j=1,2,…,6,

(B.14) $$T_t^I = 0_2 0_2',$$

(B.15) $$T_t^e = \begin{pmatrix} 0_{8\times16} & \hat{\phi}\begin{pmatrix} 0_7' & 0 \\ I_7 & 0_7 \end{pmatrix} \\ I_{16} & 0_{16}0_8{}' \end{pmatrix},$$

(B.16) $$T_t^\lambda = I_7$$

and

(B.17) $$T_t^b = I_8.$$

The (potentially) block-diagonal time-varying selection matrix, G_t, may be written as

(B.18) $$G_t = BlockDiag\left(G_t^L, G_t^S, G_t^I, G_t^e, G_t^\lambda, G_t^b\right),$$

where

(B.19) $G_t^L = \psi_t^{1/2}\begin{pmatrix} 0 \\ 1 \end{pmatrix} \otimes I_2$, where ψ is given in Section 3.4,

(B.20) $$G_t^S = I_{24},$$

(B.21) $$G_t^I = I_2,$$

(B.22) $$G_t^e = \begin{pmatrix} I_8 \\ 0_{16}\, 0_8' \end{pmatrix},$$

(B.23) $$G_t^\lambda = I_7 \text{ and}$$

(B.24) $$G_t^b = I_8.$$

The time-invariant covariance matrix of the disturbances in the transition vector equation is partitioned as

(B.25) $$Q = BlockDiag\left(Q^L, Q^S, Q^I, Q^e, Q^\lambda, Q^b\right), \text{ where}$$

(B.26) $$Q^L = \begin{pmatrix} \left(\sigma_R^{LFS}\right)^2 & \rho_R^{LFS,X}\sigma_R^{LFS}\sigma_R^X \\ \rho_R^{LFS,X}\sigma_R^{LFS}\sigma_R^X & (\sigma_R^X)^2 \end{pmatrix},$$

(B.27) $$Q^S = I_{24}\sigma_\omega^2,$$

(B.28) $$Q^I = \begin{pmatrix} \left(\sigma_I^{LFS}\right)^2 & 0 \\ 0 & (\sigma_I^X)^2 \end{pmatrix},$$

(B.29) $$Q^e = \begin{pmatrix} \sigma_{e_1}^2 & 0_7' \\ 0_7 & \sigma_e^2\, I_7 \end{pmatrix},$$ [13]

(B.30) $$Q^\lambda = I_7\, \sigma_\lambda^2$$

and

(B.31) $$Q^b = 0_8 0_8'.$$

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[13] An alternative could be to use $G_t^e = \begin{pmatrix} 1 & 0_7' \\ 0_7 & (1-\hat{\phi}^2)I_7 \\ 0_{16} & 0_{16}\, 0_7' \end{pmatrix}$ and $Q_t^e = \sigma_e^2\, I_8$, which implies estimating only one hyperparameter for the survey error.

It remains to clarify the initial conditions. The distribution of the initial state vector is given by

(B.32) $$\boldsymbol{\alpha_1} \sim N(\boldsymbol{\mu}, \boldsymbol{\Sigma}),$$

where μ and Σ denote the mean and the covariance matrix, respectively, of the initial state vector. We use diffuse initialization for most variables; see, e.g., Koopman (1997) and Koopman and Durbin (2000). In (B32), this implies setting the corresponding element in the covariance matrix $\boldsymbol{\Sigma}$ equal to infinity. For the elements related to the structural break, we use diffuse initialization for waves 2-8. For wave 1, we utilize prior information for this break from the parallel run.

The expectation of the initial state vector may be written in partitioned form as

(B.33) $$\mu = \left(\mu^{L'}, \mu^{S'}, \mu^{I'}, \mu^{e'}, \mu^{\lambda'}, \mu^{b'}\right)',$$

where

(B.34) $$\mu^L = 0_4,$$

(B.35) $$\mu^S = 0_{24},$$

(B.36) $$\mu^I = 0_2,$$

(B.37) $$\mu^e = 0_{24},$$

(B.38) $$\mu^\lambda = 0_7$$

and

(B.39) $$\mu^b = \begin{pmatrix} \mu^{b1} \\ 0_7 \end{pmatrix},$$

where μ^{b1} is the estimate of the effect of the structural break on wave 1 in the parallel survey. The covariance matrix of the initial state vector is block-diagonal and may be written as

(B.40) $\Sigma = BlockDiag(\Sigma^L, \Sigma^S, \Sigma^I, \Sigma^e, \Sigma^\lambda, \Sigma^b)$, where

(B.41) $\Sigma^L = \kappa I_4$ with $\kappa \to \infty$,

(B.42) $\Sigma^S = \kappa I_{24}$ with $\kappa \to \infty$,

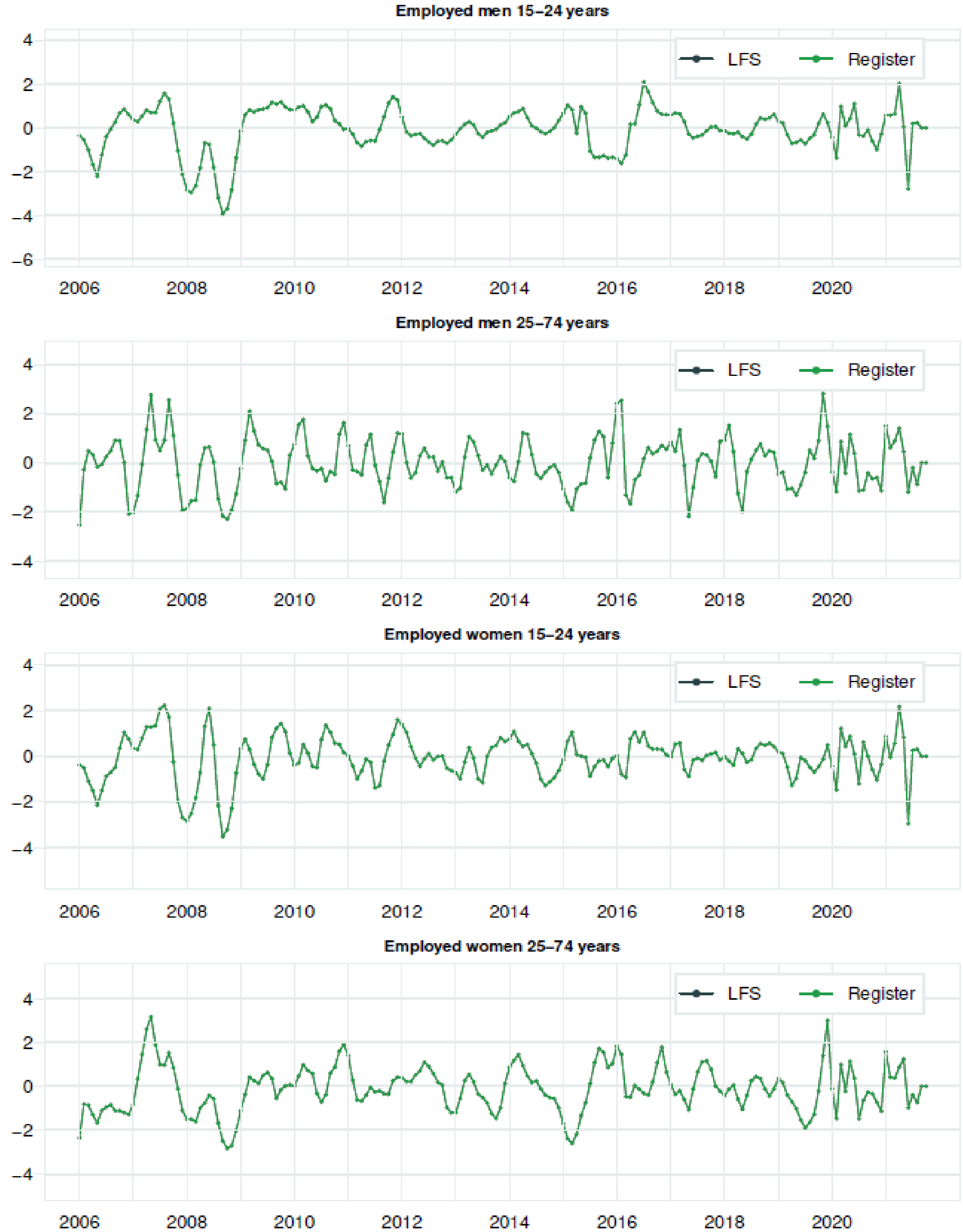
(B.43) $\Sigma^I = \kappa I_2$ with $\kappa \to \infty$,

(B.44) $\Sigma^e = I_{24}$,

(B.45) $\Sigma^\lambda = \kappa I_7$ with $\kappa \to \infty$ and

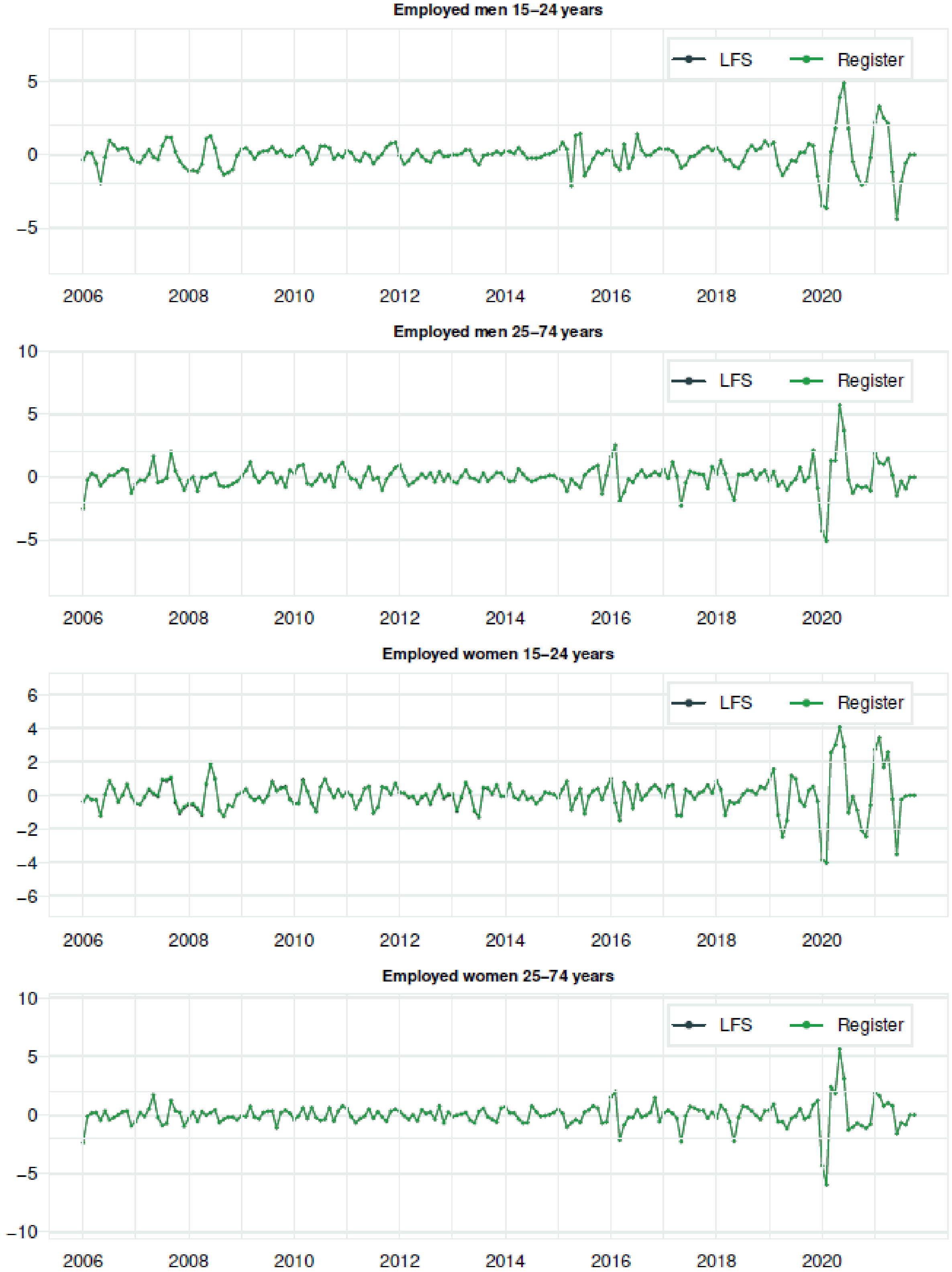
Appendix C: Graphs

Figure C.1 Auxiliary residuals for slope disturbances for employed persons by sex and age with time-varying hyperparameters.[1]



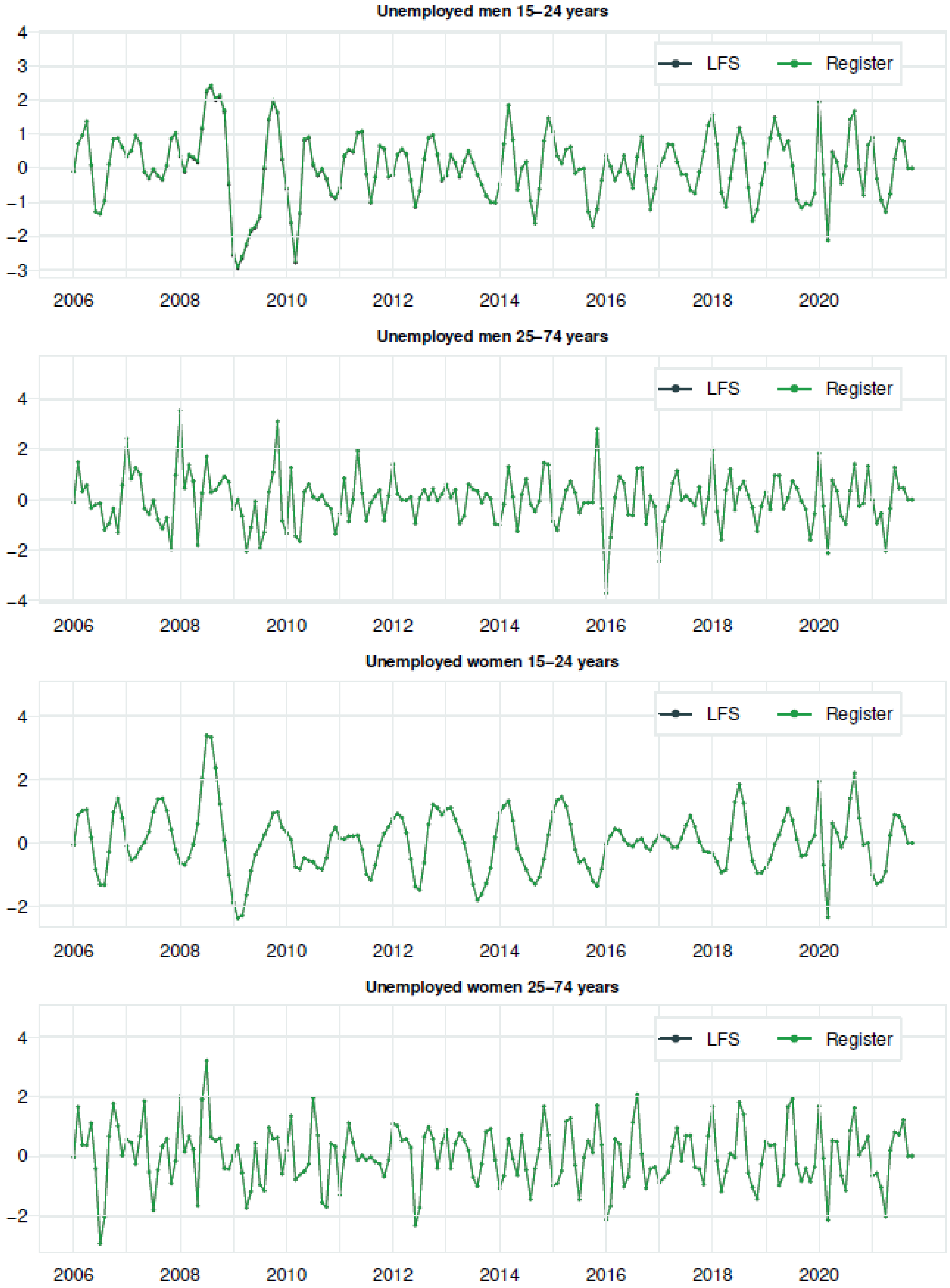
In Figure C.1, the LFS line cannot be seen, because it is almost identical to the register variable. The reason for this is that the correlation between auxiliary residuals of the slope components of the LFS and register trends is equal to or almost equal to 1.

Figure C.2 Auxiliary residuals for slope disturbances for employed persons by sex and age with time-invariant hyperparameters.[1]



In Figure C.2, the LFS line cannot be seen, because it is almost identical to the register variable line. The reason for this is that the correlation between auxiliary residuals of the slope components of the LFS and register trends is equal to or almost equal to 1.

Figure C.3 Auxiliary residuals for slope disturbances for unemployed persons by sex and age with time-varying hyperparameters.[1]



In Figure C.3, the LFS line cannot be seen, because it is almost identical to the register variable line. The reason for this is that the correlation between auxiliary residuals of the slope components of the LFS and register trends is equal to or almost equal to 1.

Figure C.4 Auxiliary residuals for slope disturbances for unemployed persons by sex and age with time-invariant hyperparameters.[1]

In Figure C.4, the LFS line cannot be seen, because it is almost identical to the register variable line. The reason for this is that the correlation between auxiliary residuals of the slope components of the LFS and register trends is equal to or almost equal to 1.

Appendix D: Some additional results

Table D.1 Smoothed 2021-redesign level shift parameter estimates and standard errors (Std. err.) for employed persons, by sex, age and wave[a]

Age	Wave	Optimal time-varying hyperparameters				Time-invariant hyperparameters			
		Male		Female		Male		Female	
		Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.
15-24	1	630	6,189	19,914	5,779	371	6,193	16,945	6,476
	2	13,227	6,050	10,912	5,819	12,967	6,058	8,199	6,532
	3	928	6,145	7,063	5,845	621	6,181	4,540	6,622
	4	-3,293	6,417	8,420	6,104	-3,639	6,502	5,999	6,757
	5	-6,381	6,337	2,624	6,194	-6,742	6,295	83	6,762
	6	-10,378	6,481	2,387	6,256	-10,741	6,424	-217	6,780
	7	148	6,516	2,350	5,998	-191	6,420	-286	6,802
	8	-7,745	6,791	11,251	6,510	-8,045	6,794	8,271	7,287
	Average	-1,608	2,252	8,115	2,145	-1,925	2,249	5,442	2,389
25-74	1	-13,846	12,560	10,314	11,570	-10,449	12,291	10,706	11,553
	2	-7,963	11,754	18,648	10,481	-4,030	10,663	18,882	10,717
	3	-7,691	11,195	18,179	10,846	-3,219	10,435	18,236	9,767
	4	1,005	10,404	13,331	10,396	6,154	9,668	13,336	8,649
	5	-2,716	10,943	12,803	10,050	2,946	9,487	12,795	9,995
	6	7,821	11,453	9,761	10,178	13,840	9,920	9,742	9,855
	7	11,994	10,811	28,813	9,981	18,554	10,264	28,736	9,589
	8	8,351	11,809	14,051	10,333	16,224	10,669	13,874	10,323
	Average	-381	4,025	15,738	3,709	5,002	3,697	15,788	3,566

[a] The period analysed is 2006M1-2021M10.

Table D.2 Smoothed 2021-redesign level shift parameter estimates and standard errors (Std. err.) for unemployed persons, by sex, age and wave[a]

Age	Wave	Optimal time-varying hyperparameters				Time-invariant hyperparameters			
		Male		Female		Male		Female	
		Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.	Estimate	Std. err.
15-24	1	3,027	4,177	7,412	3,611	4,374	3,687	7,637	3,379
	2	238	4,589	-1,342	3,962	1,818	3,976	-1,128	3,661
	3	9,819	4,716	6,364	4,046	11,391	4,127	6,558	3,738
	4	195	4,793	1,267	4,168	1,743	4,233	1,485	3,882
	5	4,599	4,801	7,844	4,204	6,128	4,258	8,118	3,932
	6	5,248	4,876	3,907	4,173	6,772	4,344	4,139	3,883
	7	689	4,901	8,217	4,138	2,232	4,360	8,452	3,846
	8	2,385	4,898	5,847	4,298	3,929	4,355	6,040	4,013
	Average	3,275	1,670	4,940	1,442	4,799	1,475	5,163	1,342
25-74	1	3,560	6,820	-2,915	5,733	4,044	6,538	-2,847	5,745
	2	-3,327	6,893	1,564	4,980	-2,772	6,514	1,693	4,984
	3	-4,527	6,711	3,576	4,852	-3,394	6,306	3,695	4,844
	4	-6,359	6,540	-1,746	4,692	-5,736	6,094	-1,625	4,703
	5	-4,878	6,492	2,077	4,663	-4,237	6,029	2,213	4,688
	6	5,650	6,540	-6,364	4,728	6,284	6,079	-6,228	4,738
	7	-3,375	6,540	754	4,770	-2,747	6,085	885	4,782
	8	842	6,542	-7,283	4,764	1,517	6,055	-7,139	4,768
	Average	-1,552	2,346	-1,292	1,736	-952	2,198	-1,169	1,739

[a] The period of the analysis is 2006M1-2021M10.

Appendix E: Additional graphs

Figure E.1: LFS estimate and register variable for employed males aged 15-24 years, in thousand.

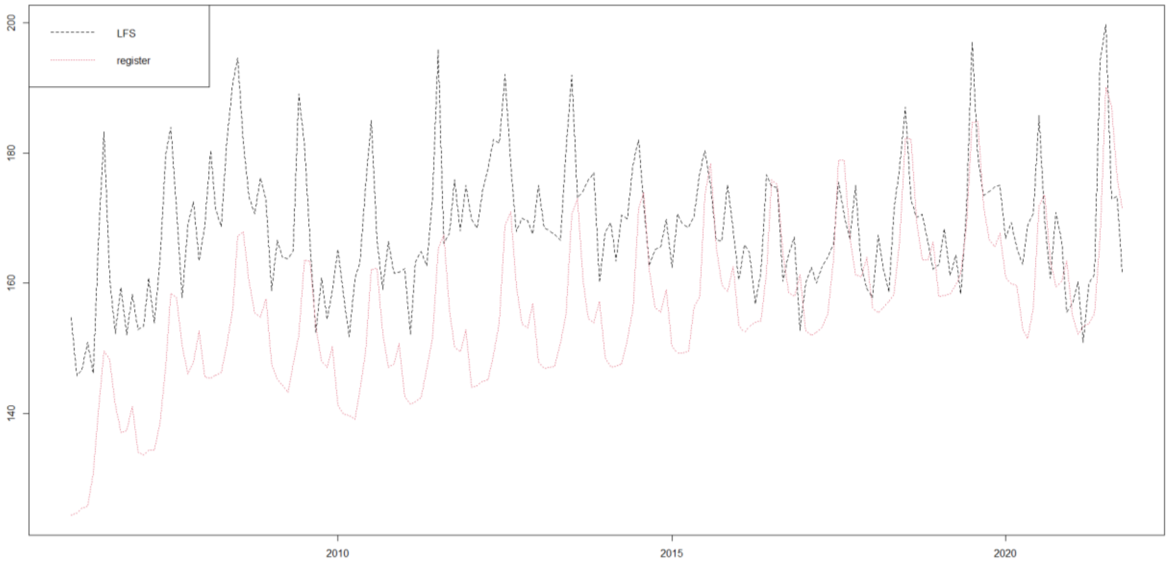


Figure E.2: LFS estimate and register variable for employed males aged 25-24 years, in thousand.

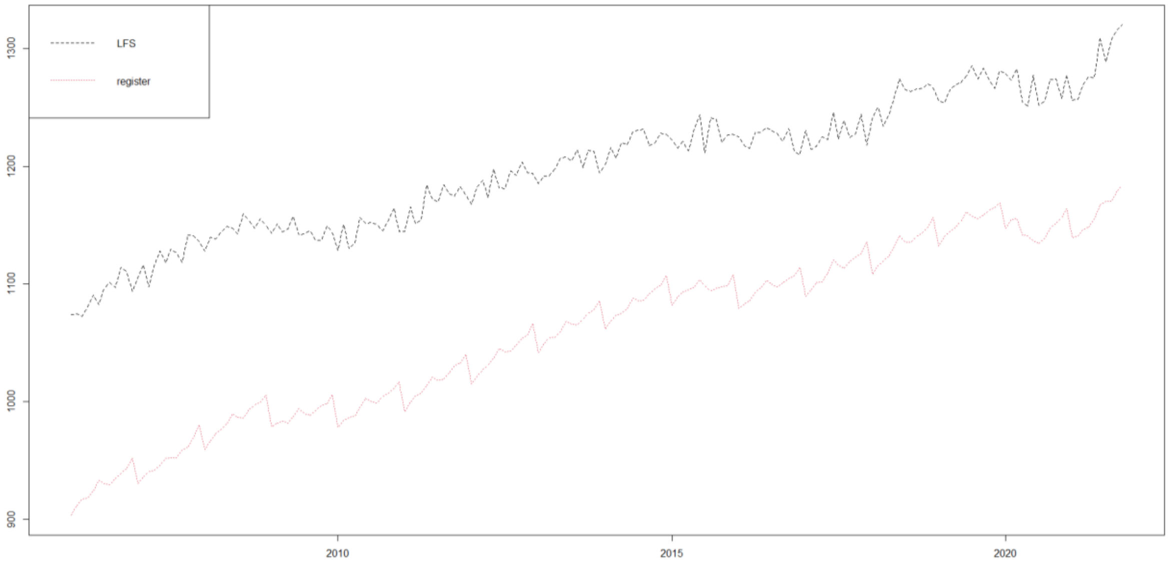


Figure E.3: LFS estimate and register variable for employed females aged 15-24 years, in thousand.

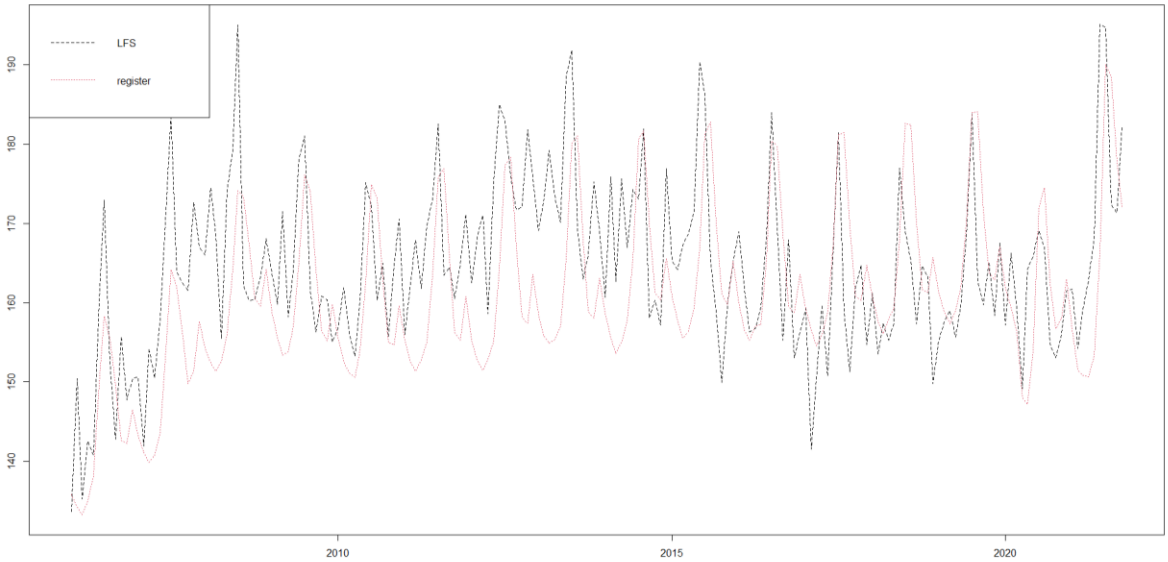


Figure E.4: LFS estimate and register variable for employed fmales aged 25-24 years, in thousand.

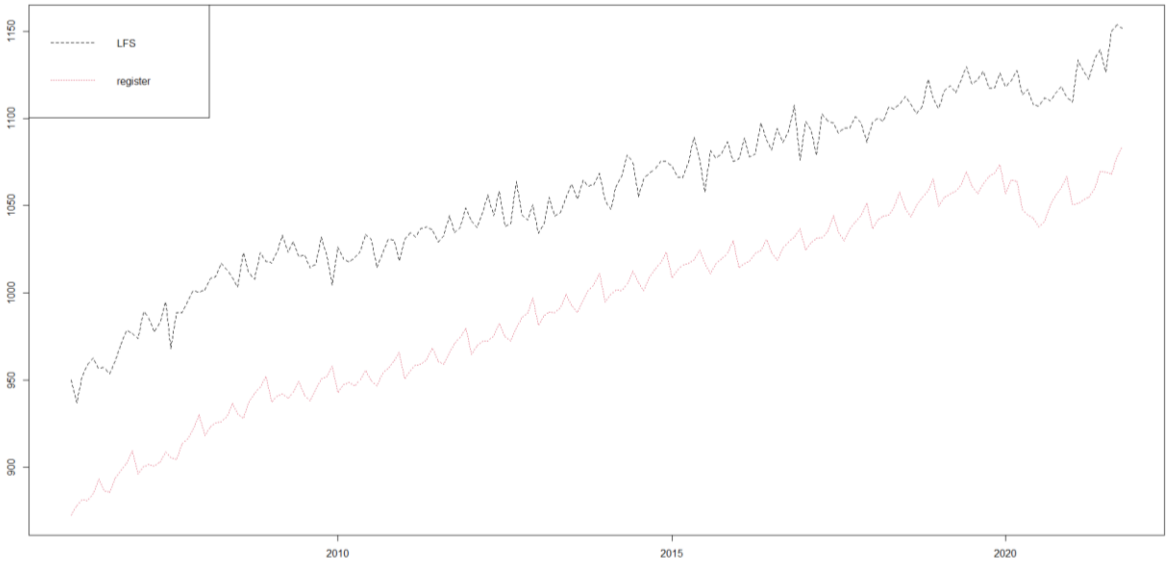


Figure E.5: LFS estimate and register variable for unemployed males aged 15-24 years, in thousand.

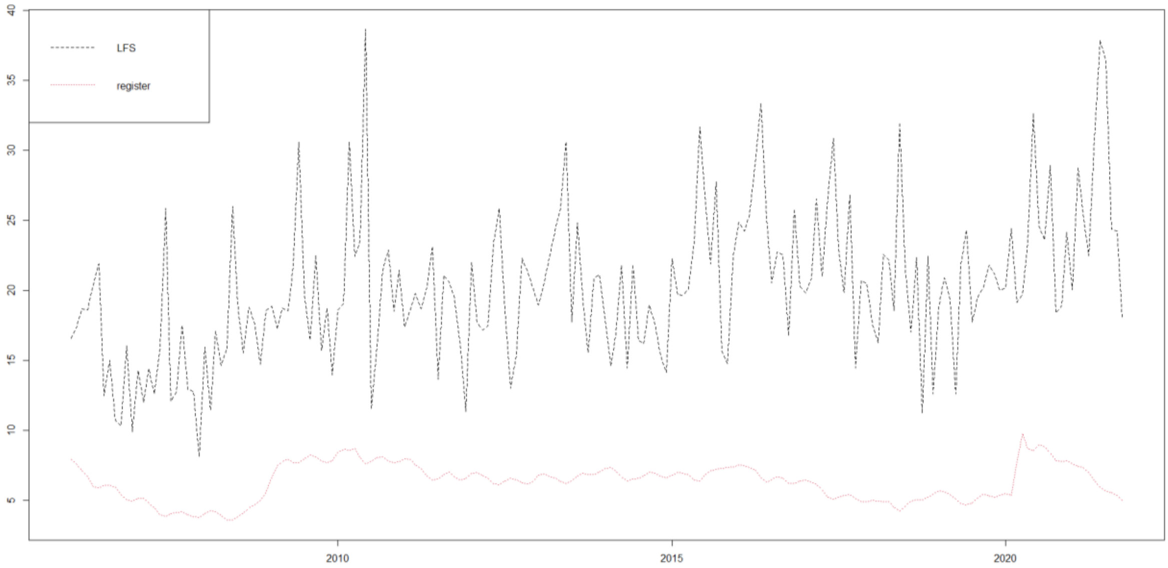


Figure E.6: LFS estimate and register variable for unemployed males aged 25-24 years, in thousand.

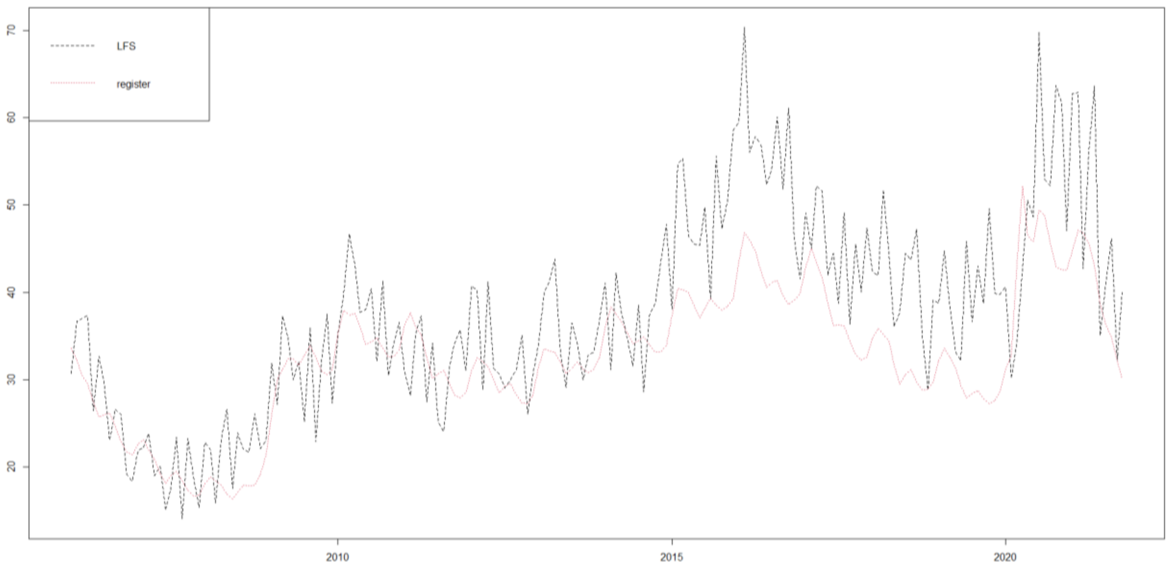


Figure E.7: LFS estimate and register variable for unemployed females aged 15-24 years, in thousand.

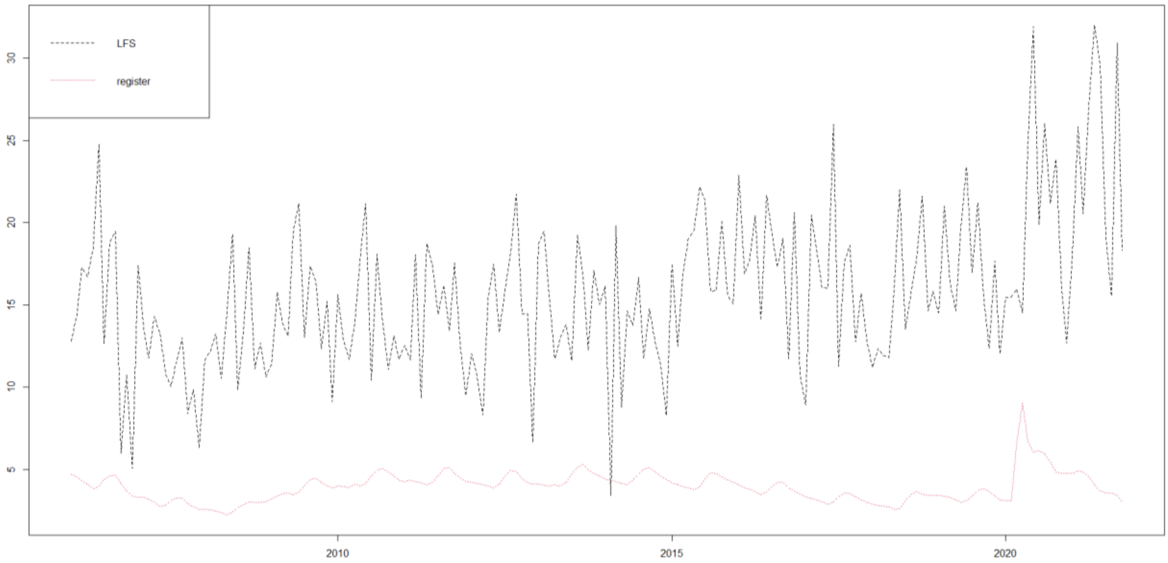


Figure E.8: LFS estimate and register variable for unemployed fmales aged 25-24 years, in thousand.