Estimation of monthly unemployment figures in a rotating panel; on the use of auxiliary series in structural times series models

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Discussion paper (201122)

Statistics Netherlands

The Hague/Heerlen, 2011

Explanation of symbols

.	= data not available
*****	= provisional figure
******	= revised provisional figure
x	= publication prohibited (confidential figure)
–	= nil or less than half of unit concerned
–	= (between two figures) inclusive
0 (0,0)	= less than half of unit concerned
blank	= not applicable
2010–2011	= 2010 to 2011 inclusive
2010/2011	= average of 2010 up to and including 2011
2010/'11	= crop year, financial year, school year etc. beginning in 2010 and ending in 2011
2008/'09–2010/'11	= crop year, financial year, etc. 2008/'09 to 2010/'11 inclusive

Due to rounding, some totals may not correspond with the sum of the separate figures.

Publisher
Statistics Netherlands
Henri Faasdreef 312
2492 JP The Hague

Prepress
Statistics Netherlands
Grafimedia

Cover
TelDesign, Rotterdam

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ISSN: 1572-0314

60083201122 X-10

Estimation of monthly unemployment figures in a rotating panel; on the use of auxiliary series in structural time series models

Summary: The Dutch Labor Force Survey (LFS) is based on a rotating panel design. Recently an estimation procedure that is based on a multivariate structural time series model has been adopted to produce monthly official statistics about the labor force. This approach handles problems with rotation group bias and small sample sizes in an effective way and enables Statistics Netherlands to produce timely and accurate estimates about the labor market. In this paper the time series model is extended by incorporating an auxiliary series about people registered as unemployed in the register of the Office for Employment and Income. The information of the auxiliary series is used to improve the precision of the monthly unemployment figures by modelling the correlation between the trends of the LFS series and the auxiliary series of the registered unemployed labor force. It appears that the trend of the series of the registered unemployed labor force is cointegrated or almost cointegrated with the trend of the estimated unemployed labor force of the LFS for several domains. This results in a considerable decrease of the standard errors for the monthly unemployed labor force.

Using the series of the registered unemployed labor force in the estimation procedure of the official monthly unemployment figures will slightly delay the timeliness of the monthly unemployment figures. The proposed model, however, can be used to produce revised unemployment figures.

Key Words: Cointegration, Kalman filter, Rotation group bias, Survey error, Small area estimation.

1. Introduction

Official monthly figures about the labor force in the Netherlands are based on a multivariate structural time series model. Statistics Netherlands implemented this estimation procedure, originally proposed by Pfeffermann (1991), in June 2010 to deal with the relatively small monthly sample sizes of the LFS and to account for the rotating panel design of the sample survey. This estimation procedure is described in Van den Brakel and Krieg (2009) and briefly reviewed in Section 2. This paper explores the possibilities to further improve this estimation technique by incorporating available auxiliary information about the number of people registered as unemployed. To this end, the trends of this auxiliary series and the LFS are compared in Section 3. The time series model, as described in Section 2, is extended in Section 4 to incorporate the auxiliary series information. Estimation results are presented in Section 5. The paper concludes with a discussion in Section 6.

2. Estimation of monthly figures about the labor force

The Dutch Labor Force Survey (LFS) is based on a rotating panel design. Each month a sample of addresses is drawn and data are collected by means of computer assisted personal interviewing (CAPI) of the residing households. The sampled households are re-interviewed by telephone (CATI) four times at quarterly intervals.

The estimation procedure of the LFS for monthly figures starts with the generalized regression (GREG) estimator, developed by Särndal e.a. (1992). There are two major problems with the rotating panel design of this survey and the way that the GREG estimator is applied in the estimation procedure. First there are substantial systematic differences between the subsequent waves of the panel due to mode- and panel effects. This is a well-known problem for rotating panel designs, and is in the literature referred to as rotation group bias (RGB). A second problem is that the monthly sample size of the LFS is too small to rely on the GREG estimator to produce timely official statistics about the monthly employed and unemployed labor force, since GREG estimators have relatively large design variances in the case of small sample sizes. To handle both problems in an effective way, a multivariate structural time series model is used to estimate official monthly statistics about the labor force.

Let Y_t^{t-j} denote the GREG estimator for the unknown population parameter, say θ_t, based on the panel observed at month *t*, which entered the survey for the first time at month *t-j*. Due to the applied rotation pattern, each month a vector $\mathbf{Y}_t = (Y_t^t \; Y_t^{t-3} \; Y_t^{t-6} \; Y_t^{t-9} \; Y_t^{t-12})^T$ is observed. As a result, a five dimensional time series with GREG estimates for the unknown population parameter is obtained. According to Pfeffermann (1991), this vector can be modeled as

$$\mathbf{Y}_t = \mathbf{1}_5 \theta_t + \boldsymbol{\lambda}_t + \mathbf{e}_t, \tag{1}$$

with $\mathbf{1}_5$ a five dimensional vector with each element equal to one, $\boldsymbol{\lambda}_t = (\lambda_t^0 \; \lambda_t^3 \; \lambda_t^6 \; \lambda_t^9 \; \lambda_t^{12})^T$ a vector with time dependent components that account for the RGB, and $\mathbf{e}_t = (e_t^t \; e_t^{t-3} \; e_t^{t-6} \; e_t^{t-9} \; e_t^{t-12})^T$ the corresponding survey errors for each panel estimate. More details about the application of this model to the Dutch LFS, including some possible extensions, is provided by Van den Brakel and Krieg (2009).

The population parameter θ_t in (1) can be decomposed in a trend component, a seasonal component, and an irregular component, i.e. $\theta_t = L_t + S_t + \varepsilon_t$, where L_t denotes a stochastic trend component, using the so-called smooth trend model, S_t a trigonometric stochastic seasonal component, and ε_t the irregular component, see for example Durbin and Koopman (2001) for details about these time series components.

The systematic differences between the subsequent waves are modeled with $\boldsymbol{\lambda}_t$ in (1). Additional restrictions for the elements of $\boldsymbol{\lambda}_t$ are required to identify the model. Here it is assumed that an unbiased estimate for θ_t is obtained with the first wave, which is observed by CAPI, i.e. Y_t^t. This implies that the first component of $\boldsymbol{\lambda}_t$ equals zero, i.e. $\lambda_t^0 = 0$ for all *t*. The other elements of $\boldsymbol{\lambda}_t$ measure the time dependent differences with respect to the first wave. To this end λ_t^j are modeled as random walks for *j* = 3, 6, 9, and 12, see Van den Brakel and Krieg (2009).

Finally a time series model for the survey errors $\mathbf{e}_t$ in (1) is developed. The rotating panel design implies sample overlap with panels observed in the past. Particularly the survey errors of the second, third, fourth and fifth wave are correlated with survey errors of preceding periods. The autocorrelations between the survey errors of the subsequent waves are estimated from the survey data, using the approach proposed by Pfeffermann et al. (1998). In this application it appears that the autocorrelation structure for the second, third, fourth and fifth wave can be modeled conveniently with an AR(1) model, Van den Brakel and Krieg (2009). Direct estimates for the variance of the series of the GREG estimators are used as prior information in the time series model using the survey error modeling approach, proposed by Binder and Dick (1990).

Time series model (1) makes optimal use of the available sample information from preceding periods to improve the GREG estimates for the monthly labor force. Furthermore, the model accounts for the rotating panel design of the LFS by modeling the RGB and the autocorrelation between the survey errors. The general way to proceed is to express the model in the so-called state space representation and apply the Kalman filter to obtain optimal estimates for the state variables, see e.g. Durbin and Koopman (2001). The state space representation of this model is given by Van den Brakel and Krieg (2009b). The software for the analysis and estimation of the time series model is developed in Ox in combination with the subroutines of SsfPack 3.0, see Doornik (1998) and Koopman, Shephard and Doornik (2008).

All state variables are non-stationary with the exception of the survey errors. The non-stationary variables are initialised with a diffuse prior, i.e. the expectation of the initial states are equal to zero and the initial covariance matrix of the states is diagonal with large diagonal elements. The survey errors are stationary and therefore initialised with a proper prior. The initial values for the survey errors are equal to zero and the covariance matrix is available from the model developed for the survey errors (Van den Brakel and Krieg, 2009). In Ssfpack 3.0 an exact diffuse log-likelihood function is obtained with the procedure proposed by Koopman (1997). Maximum likelihood estimates for the hyperparameters, i.e. the variance components of the stochastic processes for the state variables are obtained using a numerical optimization procedure (BFGS algorithm, Doornik, 1998). To avoid negative variance estimates, the log-transformed variances are estimated. More technical details about the analysis of state-space models can be found in Harvey (1989) or Durbin and Koopman (2001).

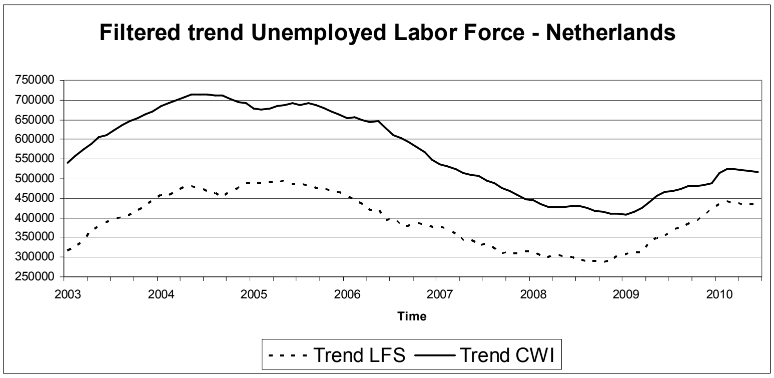
Since June 2010 this model is used by Statistics Netherlands to produce monthly official statistics about the employed and unemployed labor force for the Netherlands and a break down for age and gender in six domains. For these variables the filtered trend (L_t) and the signal ($L_t + S_t$) is published.

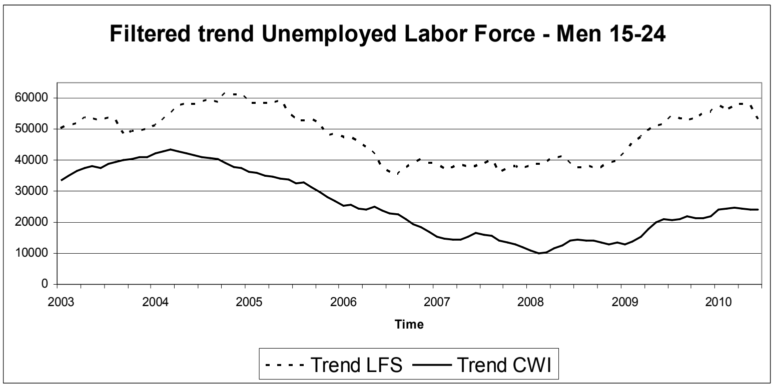
3. Auxiliary information for the unemployed labor force

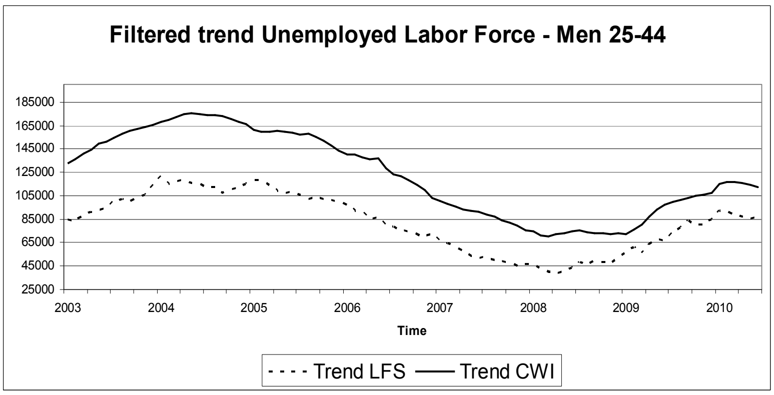
Auxiliary information about the unemployed labor force is available from the register of the Office for Employment and Income. The Dutch abbreviation is CWI, which stands for Centre for Work and Income. This name recently changed to UWV (Dutch abbreviation for Uitvoeringsinstituut voor Werknemersverzekeringen). In Figure 1, the filtered trend (L_t) from the series of the number of people registered as unemployed in the CWI, using a univariate basic structural time series model, and the filtered trend of the unemployed labor force from the time series model of the LFS are displayed for the national level and for men and women in three age classes.

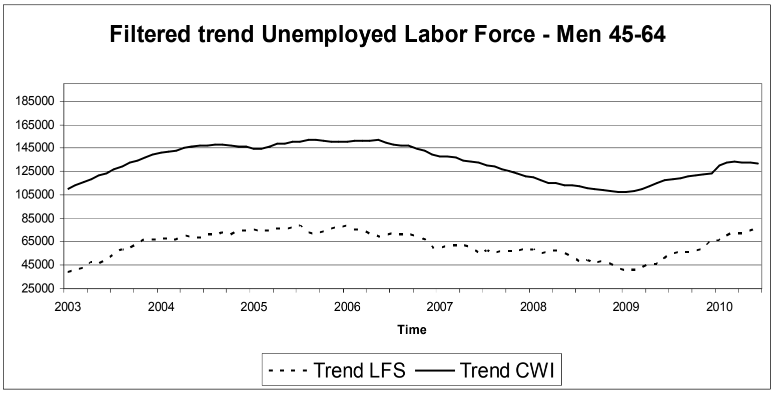
There are important differences between the unemployed labor force of the LFS and the CWI. In the LFS, a respondent is considered unemployed if he or she is actively searching for a job for at least 12 hours a week. The CWI contains people registered as being unemployed in a particular month, regardless the number of hours per week that he or she is prepared to work and the actually exercised effort to apply for jobs.

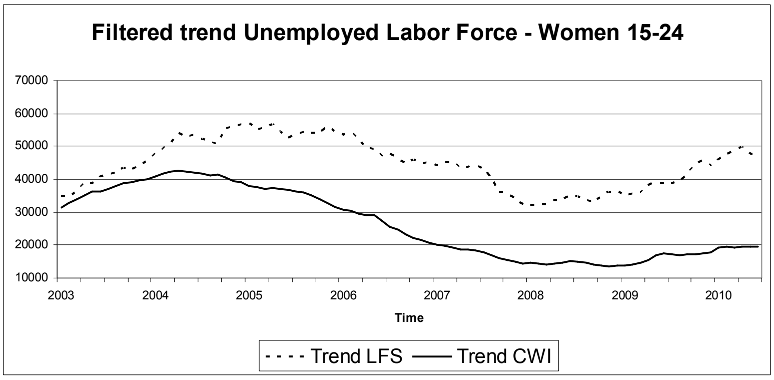
Figure 1: Filtered trends unemployed labor force Dutch LFS and people registered as unemployed in the CWI for the Netherlands and men and women in three age classes

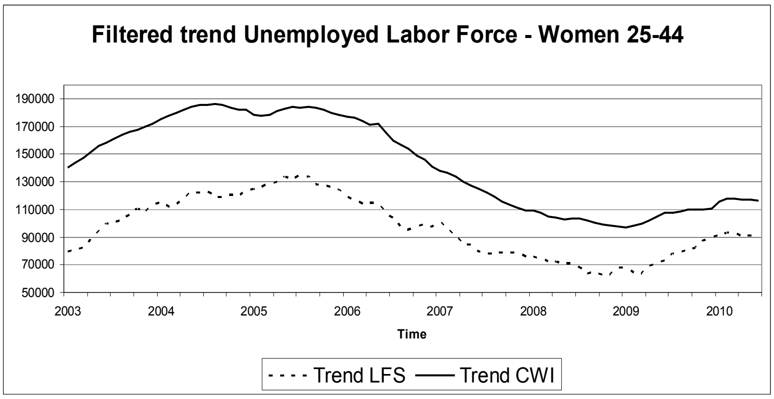


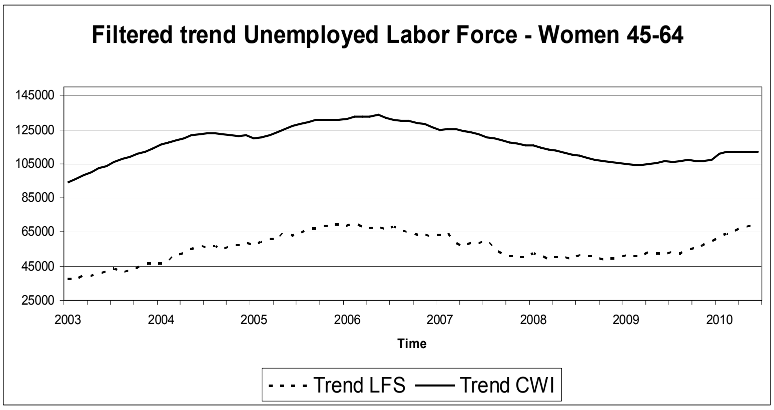












It is immediately clear that the trends of the CWI and the LFS have different levels but display more or less the same development. With the exception of the younger men and women, the level of the

CWI is larger compared to the LFS, and is a result of the aforementioned differences between CWI and LFS. The age class 15-24 does not receive a social benefit if they are unemployed and are therefore not encouraged to register at the CWI. In case these people are included in the LFS they will be nevertheless classified as unemployed labor force if they indicate that they actively search for a job. This is the reason that for the domains Men and Women 15-24, the trend of the LFS is higher compared to the trend of the CWI, while this is the opposite for the other domains.

It can nevertheless be concluded that the trends of CWI and the LFS are correlated and that it is worthwhile to investigate the possibilities to use the CWI as auxiliary information in the time series modeling approach, described in Section 2, to improve the accuracy of the estimated monthly unemployed labor force.

4. Structural time series model for a rotating panel and auxiliary series

In this section, the time series model described in Section 2 is extended to incorporate the series of the number of people registered as unemployed in the CWI. This can be accomplished in different ways. One straightforward possibility is to extend the time series model (1) for the population parameter of the LFS with a regression component for the CWI series, i.e. $\theta_t = L_t + S_t + \beta X_t + \varepsilon_t$, where X_t denotes the series available from the CWI and β the regression coefficient. The major drawback of this approach is that with this model L_t and S_t contain a residual trend and seasonal effect, because a main part of the trend and the seasonal effects in θ_t are explained by the series of CWI. This hampers the estimation of a filtered trend for the unemployed labor force of the LFS.

An alternative approach, that allows the direct estimation of a filtered trend for θ_t, is to extend model (1) with a series for the CWI and model the correlation between the trends of the series of the LFS and the series of the CWI. This gives rise to the following model:

$$\begin{pmatrix} \mathbf{Y}_t \\ X_t \end{pmatrix} = \begin{pmatrix} \mathbf{1}_5 \theta_t^{LFS} \\ \theta_t^{CWI} \end{pmatrix} + \begin{pmatrix} \boldsymbol{\lambda}_t \\ 0 \end{pmatrix} + \begin{pmatrix} \mathbf{e}_t \\ 0 \end{pmatrix}. \tag{2}$$

The series of the LFS and the CWI both have their own population parameter that can be modeled with two separate time series models, i.e. $\theta_t^z = L_t^z + S_t^z + \varepsilon_t^z$, where z = LFS or z = CWI, L_t^z a smooth trend model, S_t^z a trigonometric seasonal component and ε_t^z white noise to model the unexplained variation. Since CWI is based on a registration, this series does not have a RGB or a survey error component. Therefore, the observed series X_t is equal to the population parameter θ_t^{CWI}.

The smooth trend model for the LFS and the CWI is defined as $L_t^z = L_{t-1}^z + R_{t-1}^z$, with $R_t^z = R_{t-1}^z + \eta_t^z$, with $\eta_t^z \cong N(0, \sigma_{\eta z}^2)$. L_t and R_t are often referred to as the level and slope parameter. The model allows for correlation between the disturbances of the trend of the LFS and the CWI, by assuming that $\mathrm{cov}(\eta_t^{CWI}, \eta_t^{LFS}) = \rho \, \sigma_{\eta CWI} \, \sigma_{\eta LFS}$, with ρ the correlation coefficient between these series. The correlation between both series is determined by the model. If the model detects a strong correlation between the trends of the CWI series and the LFS series, then the trends of both series will develop into the same direction more or less simultaneously. In this case the additional information from the auxiliary series will result in an increased precision of the filtered estimates for the monthly unemployment figures.

In this application, the trigonometric seasonal components for CWI and LFS are time independent, as will follow from the results in section 5. Therefore it is not useful to allow for correlation between the disturbances of the seasonal components for CWI and LFS.

In the state-space representation of (2), the covariance matrix of the transition equation, say $\mathbf{Q}$, is implemented as

$$\mathbf{Q} = \mathbf{ADA}^t, \tag{3}$$

with **D** a diagonal matrix and **A** a lower triangular matrix with ones on the diagonal. As a result the variances of the noise of the trend of the LFS and the CWI, are implemented as $\sigma_{\eta LFS} = \exp(d_{\eta LFS})$ and $\sigma_{\eta CWI} = a^2_{\eta LFS,\eta CWI} \exp(d_{\eta LFS}) + \exp(d_{\eta CWI})$, with $d_{\eta LFS}$ and $d_{\eta CWI}$ the corresponding diagonal elements of **D** for the variances of the noise of the trend of the LFS and the CWI and $a_{\eta LFS,\eta CWI}$ the corresponding off diagonal element of **A** for these disturbance terms. The covariance between the noise of the trend of the LFS and the CWI, is implemented as $\mathrm{cov}(\eta_t^{CWI}, \eta_t^{LFS}) = a_{\eta LFS,\eta CWI} \exp(d_{\eta CWI})$. If the trends of the CWI and the LFS series are cointegrated then $\exp(d_{\eta CWI}) \to 0$ and $\mathrm{cor}(\eta_t^{CWI}, \eta_t^{LFS}) \to 1$. Decomposition (3) ensures that the maximum likelihood estimate for **Q** is always positive-semidefinite and avoids numerical problems if the maximum likelihood estimates for $\mathrm{cor}(\eta_t^{CWI}, \eta_t^{LFS})$ tend to the boundary of the parameter space.

5. Results

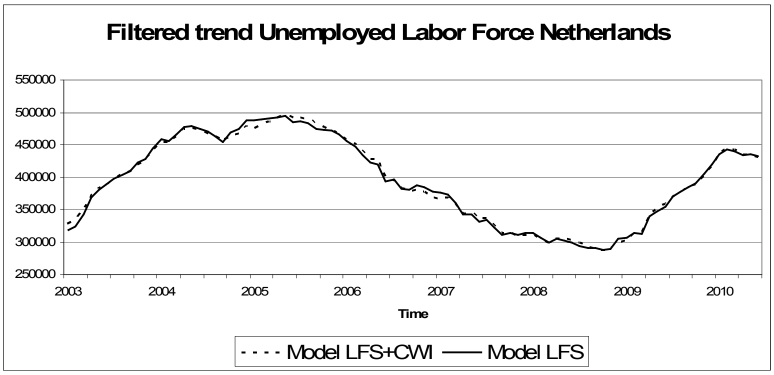
Time series models (1) and (2) are used to estimate the monthly unemployed labor force and the results are compared to quantify the effect of the CWI information on the point estimates and the standard errors. Figure 2 compares the filtered trend and the standard errors of the unemployed labor force for the national level and the domains of men and women in three age classes based on a model with and without CWI. Note that the filtered trend for the LFS in figure 2 is the same as the filtered trend for the LFS plotted in Figure 1.

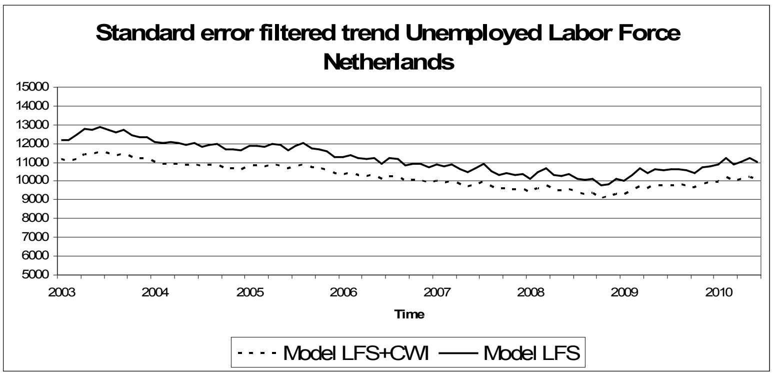
In Table 1, the correlation ρ between the noise of the trends of the LFS and the CWI is specified. Also the mean of the relative absolute difference (MARD) of the filtered trend and the mean of the relative difference (MRD) of the standard errors between model (1) and (2) for the monthly unemployed labor force are specified for the national level and the series for age and gender in six domains. These means are defined as

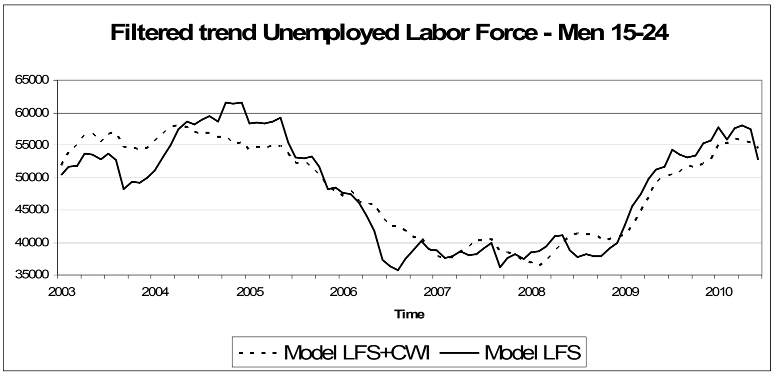
$$MARD(L) = \frac{1}{T}\sum_{i=1}^{T} \frac{\left|L_t^{(1)} - L_t^{(2)}\right|}{L_t^{(1)}} \times 100, MRD(SE) = \frac{1}{T}\sum_{i=1}^{T} \frac{SE_t^{(1)} - SE_t^{(2)}}{SE_t^{(1)}} \times 100, \tag{4}$$

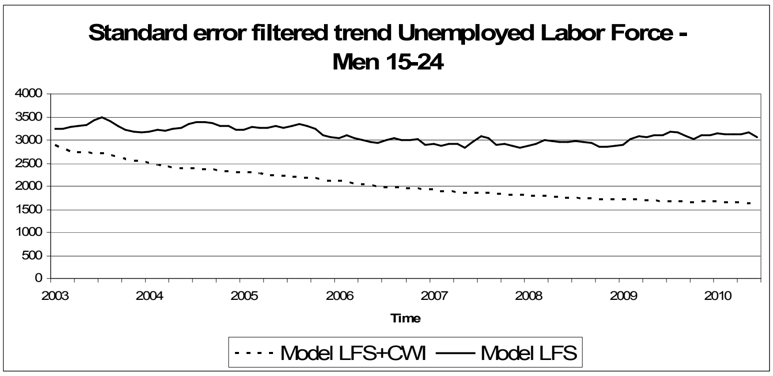
where L is the filtered trend and SE the standard error of the filtered trend at month t and the superscript refers the formula number of the applied time series model.

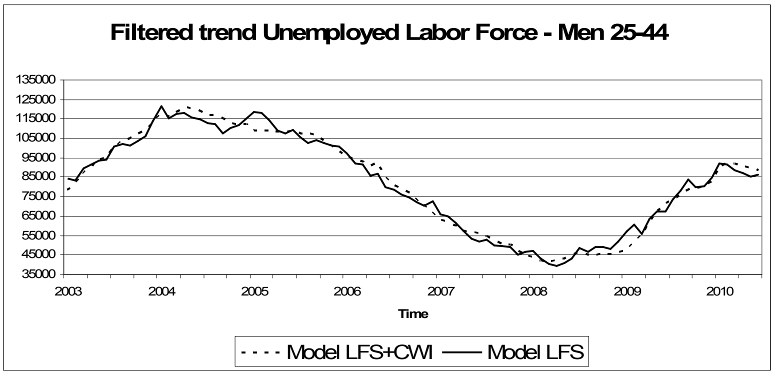
Figure 2: Filtered trend with standard errors of the unemployed labor force at the national level based on times series model (1) and (2)

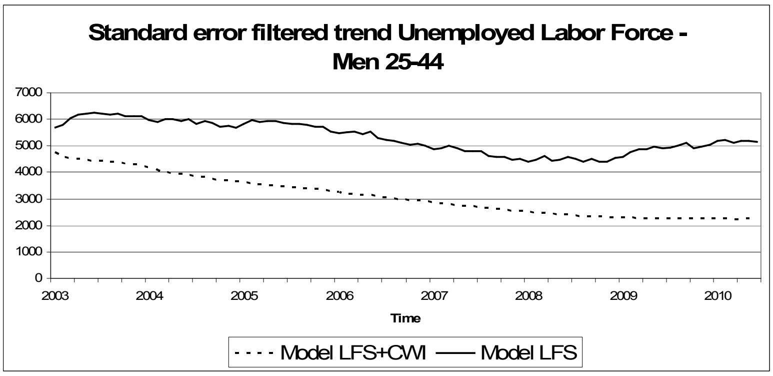









Filtered trend Unemployed Labor Force - Men 25-44
Time
Model LFS+CWI
Model LFS


Standard error filtered trend Unemployed Labor Force - Men 25-44
Time
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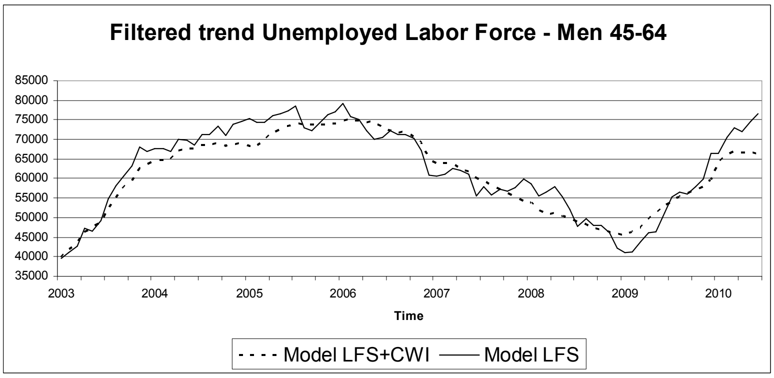
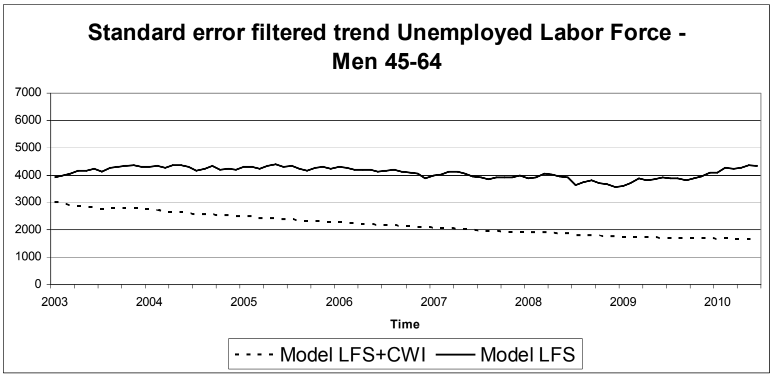
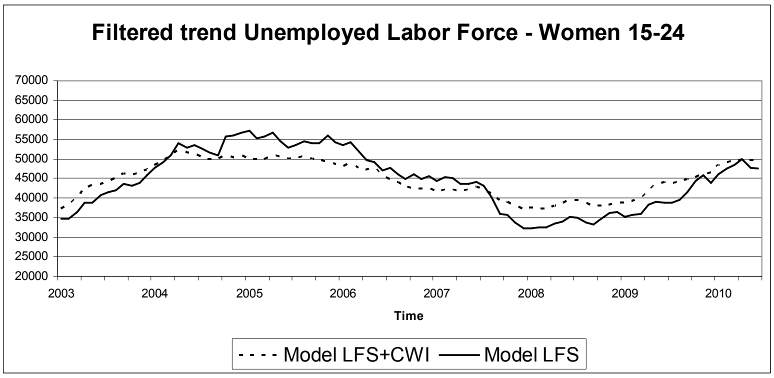
Model LFS


Filtered trend Unemployed Labor Force - Men 45-64
Time
Model LFS+CWI
Model LFS


Standard error filtered trend Unemployed Labor Force - Men 45-64
Time
Model LFS+CWI
Model LFS


Filtered trend Unemployed Labor Force - Women 15-24
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45000
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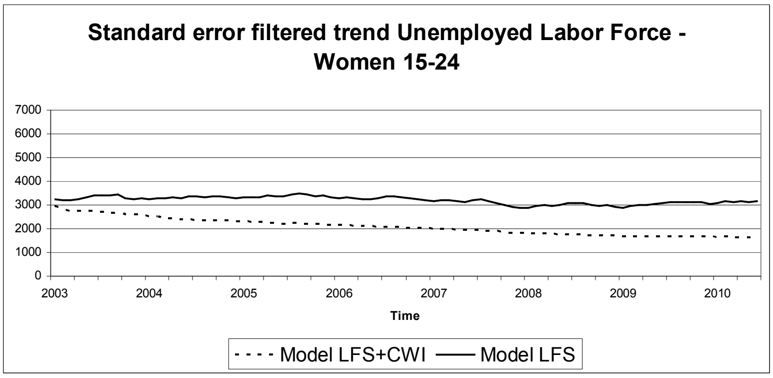
Standard error filtered trend Unemployed Labor Force - Women 15-24
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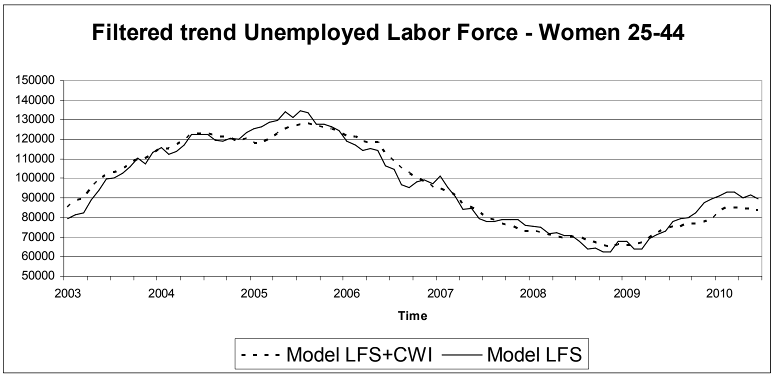
Filtered trend Unemployed Labor Force - Women 25-44
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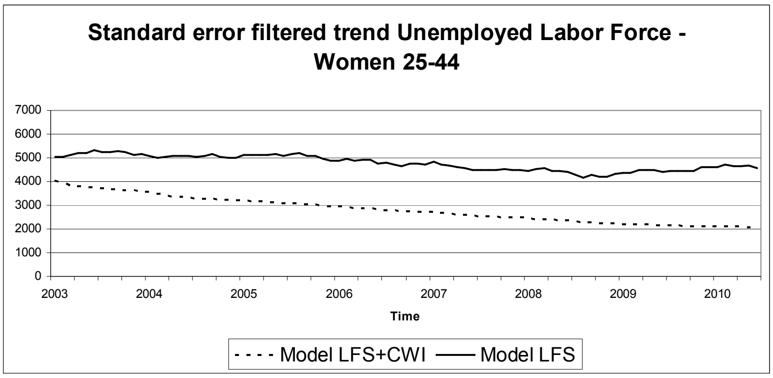
Standard error filtered trend Unemployed Labor Force - Women 25-44
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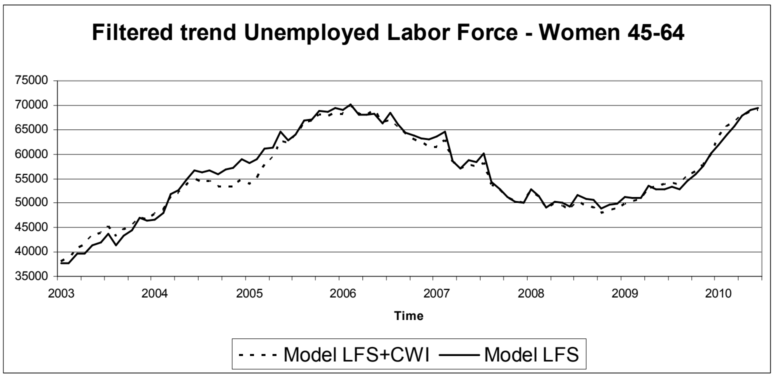


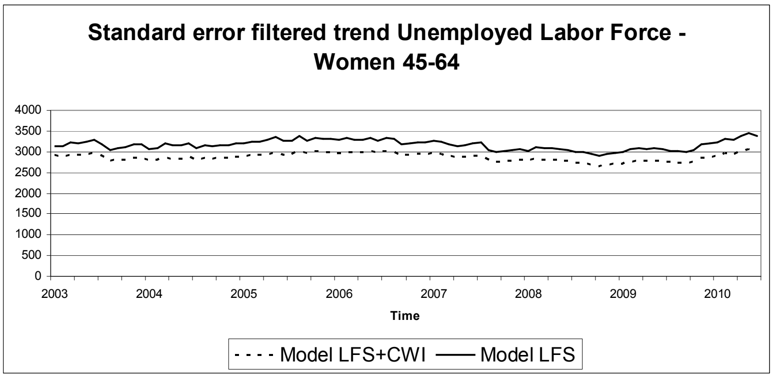


Table 1: Estimated correlation between the trend of CWI and the LFS and the MARD for the filtered trend and the standard error of the unemployed labor force over the last 30 months at the national level and a classification into gender and age in six domains

Domain	Correlation trend	MARD filtered trend	MRD standard error
Netherlands	0.88	0.63	7.77
Men – 15-24	1.00	4.91	43.54
Men – 25-44	1.00	4.96	51.26
Men – 45-64	1.00	6.50	55.08
Women – 15-24	1.00	8.26	43.95
Women – 25-44	1.00	4.80	50.16
Women – 45-64	0.92	1.44	9.24

Striking is the difference between the effect of the CWI series at the national level on the one hand and the domains on the other hand. The filtered trend for the Netherlands is hardly influenced by the CWI series and the reduction of the standard errors is relatively small. The impact of CWI on the filtered trends as well as the standard errors for the domains is, on the other hand, substantial. In these cases the CWI also has a stabilizing effect on the filtered trend estimates. Indeed, the filtered trends for the domains based on the model with CWI are more smoothed compared to the filtered trend based on a model for the LFS data only.

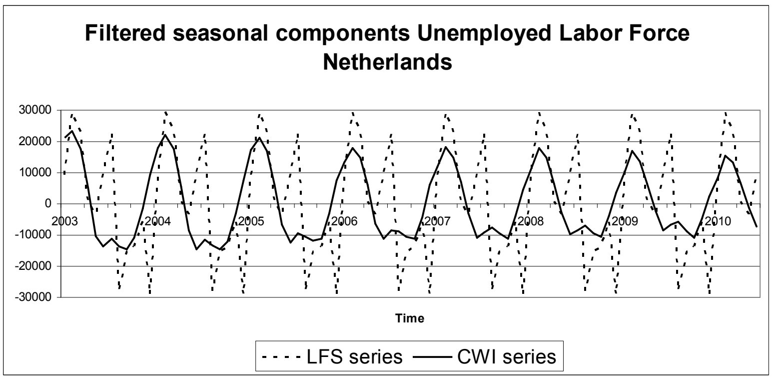
The difference of the effect of CWI at the national level and a breakdown in six domains is also reflected by the estimated correlation between the trend of the CWI and the trend of the LFS. For the domains both trends are cointegrated or almost cointegrated, resulting in substantial standard error reductions, with the exception of the women 45-64. The correlation between trends of CWI and the LFS at the national level is strong, but substantially smaller compared to the domains.

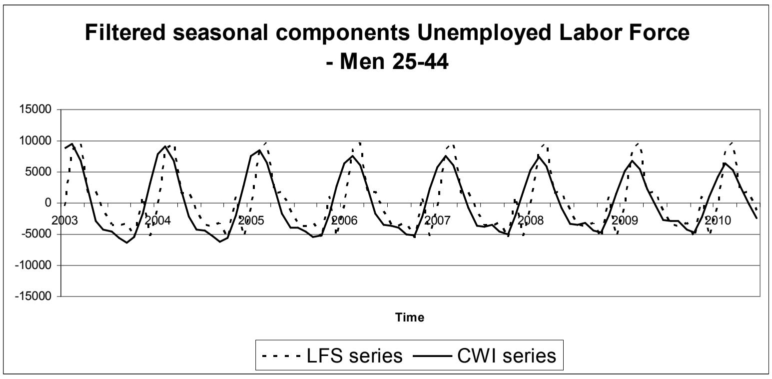
The standard errors of the filtered trends under model (1) are more or less proportional to the level of the trends. This is for example reflected by a small increase of the standard error during the economic depression after 2009. This proportionality is caused since the variance of the GREG estimates of the observed series taken proportional to the level of these estimates. Since the survey errors $\mathbf{e}_t$ in the time series model are proportional to the variances of the GREG estimates of the observed series, the standard error of the filtered trend is also proportional to the level of the trend. For the domains with cointegrated trends, the standard errors of the trend under model (2) reflect a steady decrease and are clearly not proportional to the level of the trend. In the case of cointegrated trends, the additional information from the auxiliary series is apparently so influential that the standard error of the filtered trend is not influenced by the level of the standard errors of the GREG's in the time series component of the survey errors. The steady decreasing pattern of the standard errors of the filtered estimates under model (2) indicates that the Kalman filter is picking up new information if new data becomes available.

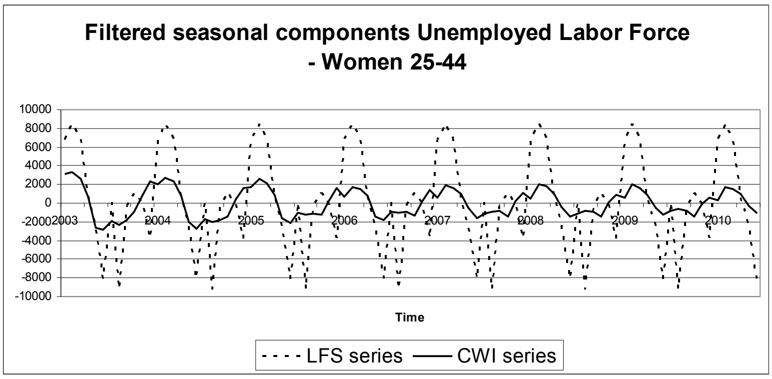
In the Annex, the filtered estimates of the unemployed labor force based on model (1) and model (2) are compared for the national level and for the six domains. The results are similar as for the trend estimates shown in Figure 2, with a substantial impact of CWI on the point estimates and the standard errors for the domains.

The seasonal components in the series of the LFS as well as the CWI are time invariant. Models that allow for correlation between the disturbances of the seasonals of the LFS and the CWI are therefore not considered. In Figure 3 the filtered estimates for the seasonal component of the LFS and the CWI series based on model (2) are shown for the Netherlands at the national level and the domain for men 25-44 and women 25-44.

Figure 3: Filtered seasonal components of the unemployed labor force at the national level, men 25-44 and women 25-44 based on times series model (2)







The underlying model assumptions of the state-space model are that the disturbances of the measurement equation and the transition equation are normally distributed and serially independent with constant variance. Under this assumption, the standardized prediction errors are also normally and independently distributed with constant variance. Standard diagnostic tests summarized by Durbin and Koopman (2001), section 2.12, do not indicate that these assumptions are not met under both models. To test whether the correlation between the trend of the LFS and the CWI is "real", the CWI series and the LFS series of different domains are combined in model (2). If fore example the CWI series of Women 15-24 is combined with the LFS data of the national level or the Men 25-44, then the correlation drops to 0.21 and 0.39 respectively.

6. Conclusions

The Dutch LFS employs a multivariate structural time series model to publish official statistics about the labor force on a monthly basis. Extending this model with the series of registered unemployment, which is available from the CWI, clearly improves the estimates for the monthly unemployed labor force. The gains are substantial for the series of domains based on a classification into age and gender in six categories. The gains for the series at the national level are smaller. One reason is that the sampling error is substantially smaller in the LFS series at the national level compared to the LFS series for the six domains. As a result the series of CWI add more information to the LFS series for the domains. Another possible explanation is that the correlation between trend of the CWI and the LFS in the domains is substantially larger than at the national level. In the domains the trends are cointegrated, with the exception of the women 45-64. The relationship between the series of the LFS and the CWI is the strongest for the age class 25-44, since unemployed people must register at the CWI to receive social benefits and have a job-search requirement to receive this benefit. The relationship is weaker in the age class 15-24 since this group does not receive a social benefit if they are unemployed and are therefore not encouraged to register at the CWI. If these people are included in the LFS they are nevertheless classified as unemployed labor force if they indicate that they actively search for a job. The relationship is also weaker for the age class 45-64, since unemployed people at an age of 58 and over are registered at the CWI to receive social benefits but are not obliged to search for a job. If these people are included in the LFS they are not classified as a member of the labor force since they are not actively searching for a job. Nevertheless, a correlation of 1 is found for almost al domains. At the national level, however, the relationships of the different domains are mixed, which might explain the smaller correlation at the national level.

Amendments of the law with respect to unemployment benefits and social benefits or sudden changes in the mode of operation of the CWI might give rise to discontinuities in the series. As a result, the evolution of the CWI series does not reflect the real development of the unemployed labor force. A consequence of extending the time series model with the auxiliary series of the CWI is that discontinuities in this auxiliary series affect the monthly estimates of the unemployed labor force and will influence the evolution of these series incorrectly. Such situations should not hamper the application of the CWI series as auxiliary information, since this kind of discontinuities can be modeled via an appropriate intervention variable, see e.g. Van den Brakel and Roels (2010) for details.

Currently the use of the CWI series in the estimation approach would slightly delay the timeliness of the monthly unemployment figures since the CWI figures about the latest month become available a few days before Statistics Netherlands publish the monthly labor force figures. Another possibility is to use the CWI information to produce revised unemployment figures. A change-over to a model that incorporates the CWI series as auxiliary information probably requires a revision of the series that is currently used to publish official monthly unemployment figures.

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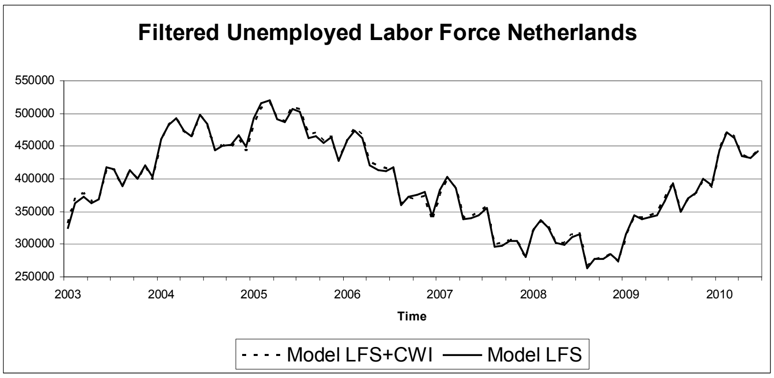
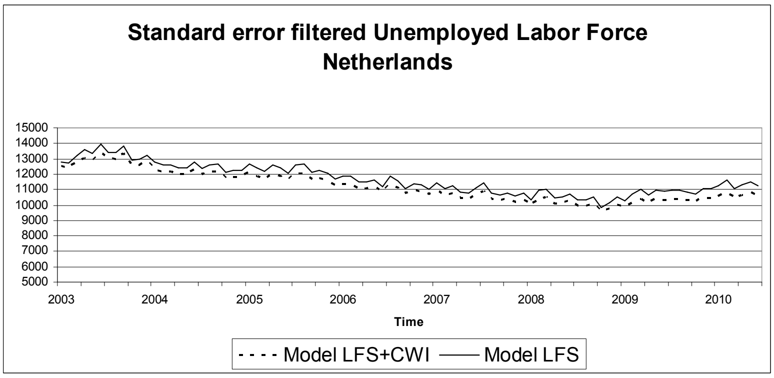
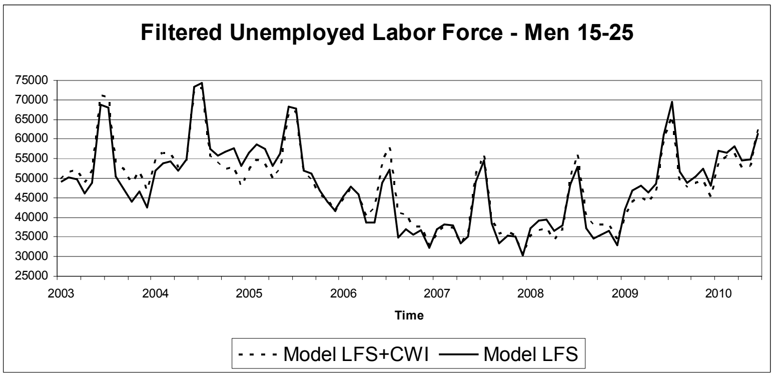
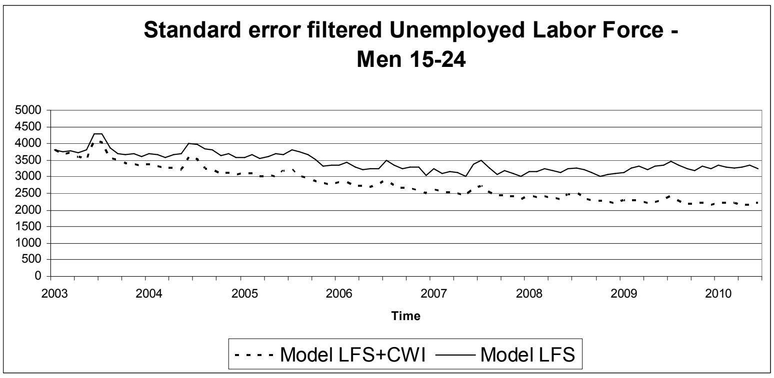
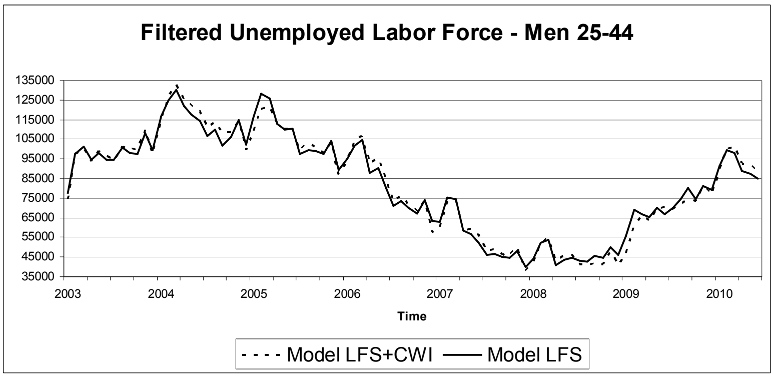
Annex : Filtered estimates monthly unemployed labor force







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135000
125000
115000
105000
95000
85000
75000
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55000
45000
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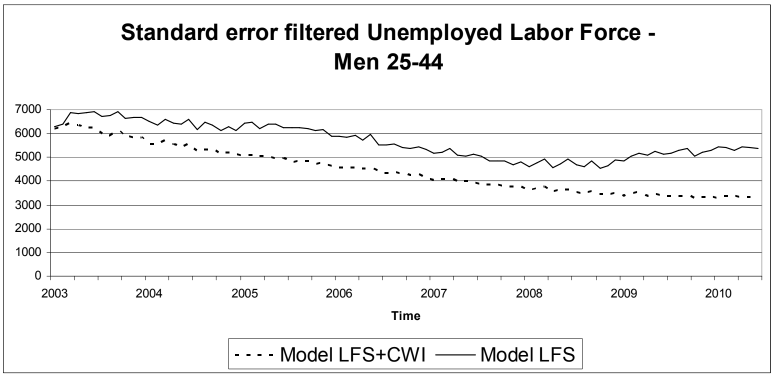
2003
2004
2005
2006
2007
2008
2009
2010
Time
Model LFS+CWI
Model LFS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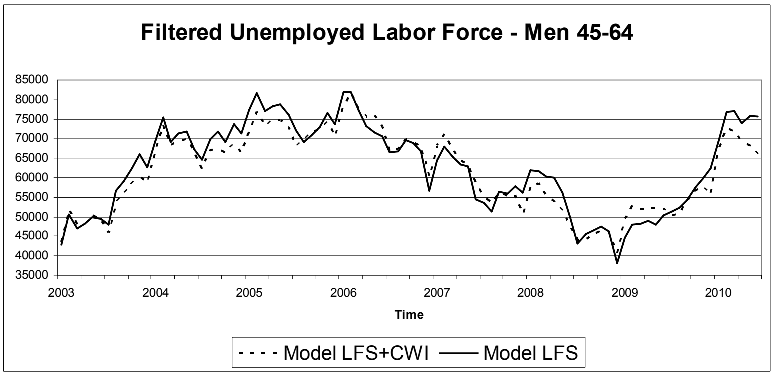
Time
Model LFS+CWI
Model LFS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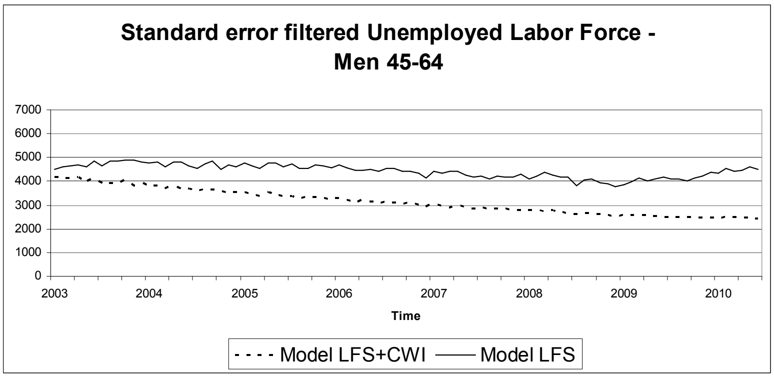
Model LFS+CWI
Model LFS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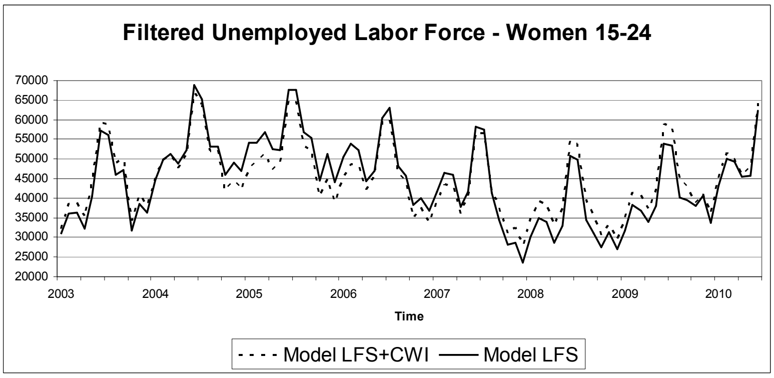
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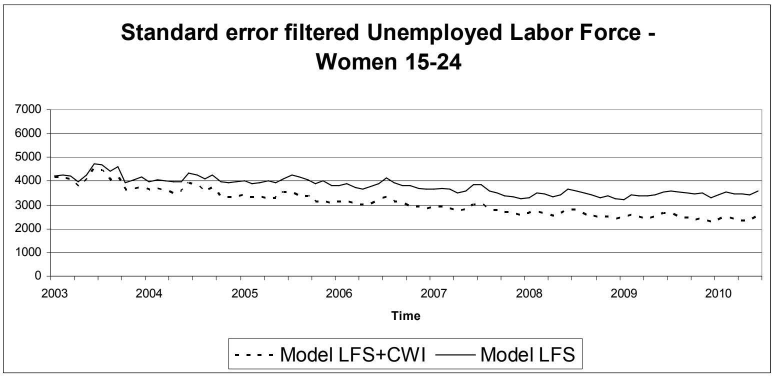
Time
Model LFS+CWI
Model LFS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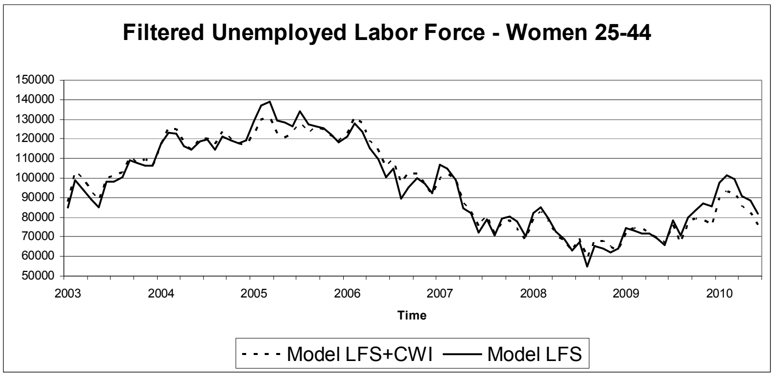
Time
Model LFS+CWI
Model LFS


Filtered Unemployed Labor Force - Women 25-44
150000
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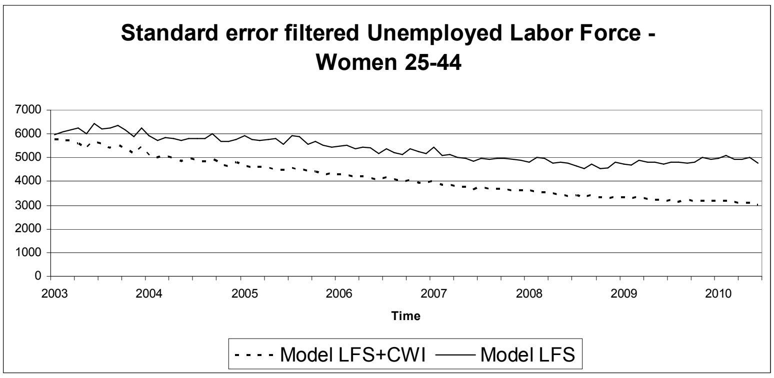
Time
Model LFS+CWI
Model LFS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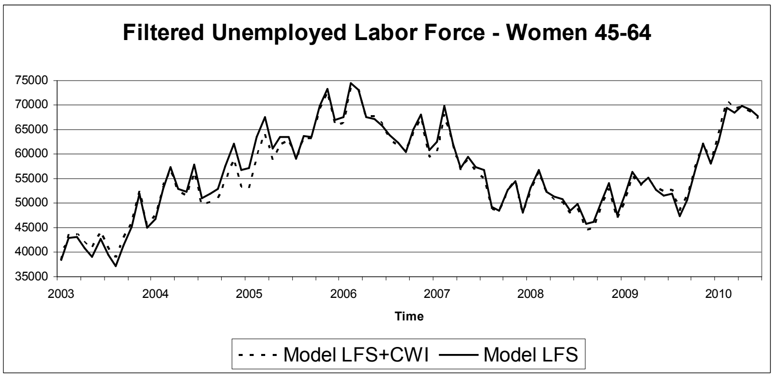
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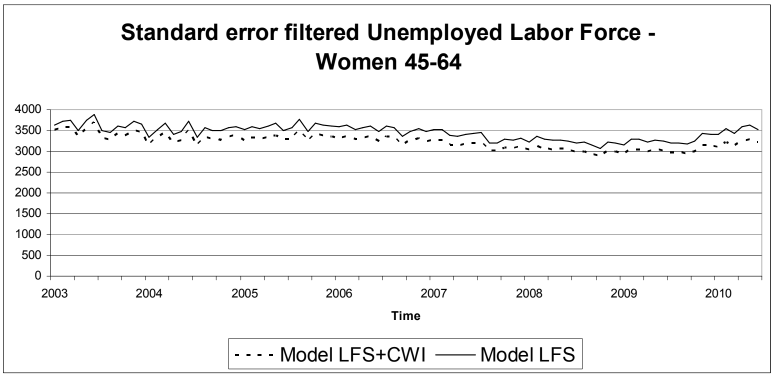
Model LFS


Standard error filtered Unemployed Labor Force - Women 45-64
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2010
Time
Model LFS+CWI
Model LFS