LABOUR AND EDUCATION STATISTICS

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Statistiska centralbyrån Statistics Sweden

Flow statistics

– an early indicator of turning points on the labour market?

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Foreword

The objective of the Swedish Labour Force Survey (LFS) is to describe the current employment conditions for the entire population aged 15-74 and to give continuous monthly, quarterly and annual information on the development of the labour market.

One way of describing labour market developments is by net changes in various labour market indicators between a given time and the corresponding period one year before. These net changes are functions of various gross flows.

This report presents a study of the correlations between net changes in the employment and unemployment stocks and labour market flows. The report shows that these correlations can be used to obtain indicators which show turning points in various labour market indicators 3-6 months earlier than what can currently be done.

The study and the report was conducted and written by Jan Selén and Andreas Poldahl. Anna Broman has been in charge of the editorial work.

We hope this report will provide a basis for continuous production of indicators which can show changes in the labour market a few months earlier than is possible today.

Statistics Sweden April 2015

Inger Eklund

Hassan Mirza

A note of thanks

We would like to express appreciation to our survey respondents – the people, enterprises, government agencies and other institutions of Sweden – with whose cooperation Statistics Sweden is able to provide reliable and timely statistical information meeting the current needs of our modern society.

Contents

1. Summary

The analysis in this report is based on employment and unemployment *stocks* and on labour market *flows* from the Swedish labour force survey (LFS). Monthly as well as and quarterly data are examined. The flows show transitions between different states in the labour market, known as gross flows between adjacent quarters or between months three months apart.

The associations between the changes in the number of persons employed as well as the number of persons unemployed and the flows in the labour market during the period 1993 to 2012 are analysed. The relationships for various flow indicators to the number of persons employed or the number of persons unemployed differ, but there are also differences between business cycles.

As regards the flows to unemployment from temporary employment and to temporary employment from unemployment, effects on both unemployment and employment were found. The flows to temporary contracts seem to precede the turn in the level of number of persons unemployed by 3-4 quarters; correspondingly, they precede the turn in the level of number of persons employed. The results are based on quarterly data for the 16-64 age group, and analyses for the cohort 16-24 years of age provide similar conclusions. However, estimates based on monthly data provide uncertain and unclear results.

According to estimation results for those aged 16-24, associations between the flow to temporary employment from unemployment and the level of unemployment were found. The correlation is negative and statistically significant for all quarterly lags except for the third quarter. This result is also verified, to some extent, for those aged 16-64. When there is an effect from the flow to unemployment from temporary employment and the change in employment level, the effect is negative. The time lag in the latter case is up to 3 quarters.

Analyses of associations between long-term trends in the flow indicators and trends in the number of persons employed or the number of persons unemployed provide some results. Exogenous disturbances in the flow to temporary employment exhibit a positive respectively negative effect on the future gap of number of persons employed respectively number of persons unemployed. The gaps in employment and in the number of unemployed is highest between 2-4 quarters after a shock in flows has occurred, and then the trends return to normal levels.

2. Introduction

The present report focuses on employment stocks linked to flows in and out of unemployment. There are reasons to believe that flows in the labour market may provide an early indication of a turning point in the level of employment. The issue can be studied using flow statistics from the Labour Force Survey (LFS). A further question is whether changes in these flows may indicate change in future economic activity generally. The aim of this report is to examine whether flow indicators can be used as a forecasting tool for the labour market.

Search models are used in labour economics for an understanding of how unemployment and job vacancies occur simultaneously. Such models have also been used to explain how macroeconomic shocks affect the labour market through the creation of new jobs and the destruction of existing jobs, and how changes in employment and unemployment levels are affected.

An alternative to standard search models is a model based on stock-flow matching, see Ebrahimy and Shimer (2010). Their model is based on the inflow of unemployed, the stock of jobs, the inflow of job openings and the stock of unemployed. In an interesting analysis, Shimer (2012) compared the importance of variations in the relative flows from unemployment to employment with the variations in the corresponding flows from employment to unemployment, in the case of changed proportions of unemployed and employed persons. It turns out that the importance of transitions from unemployment to employment is at least double compared with the opposite for the United States.

In this report, the flows are studied in relation to stocks in the labour market over time. The analysis has similarities to stock-flow matching without direct ties.

The report was commissioned by the LFS unit at Statistics Sweden. The project team included Andreas Poldahl and Jan Selén, both from Statistics Sweden.

3. Basic data

3.1 LFS data

The Swedish Labour Force Survey (LFS) has a rotating panel design. An individual in the survey participates every third month during a period of two years. Every month the oldest rotation group is included for the eighth and last time, while a new rotation group is introduced. The flow statistics show transitions between different states in the labour market, known as gross flows based on the 7/ 8 of the sample in a given month which is recurring in the LFS three months later (January to April, February to May, etc.). By merging observations from the three months of a quarter average, quarterly stocks and average flows between quarters are estimated. Table 3.1 explains the main variables used in our analysis.

Table 3.1
List of variables

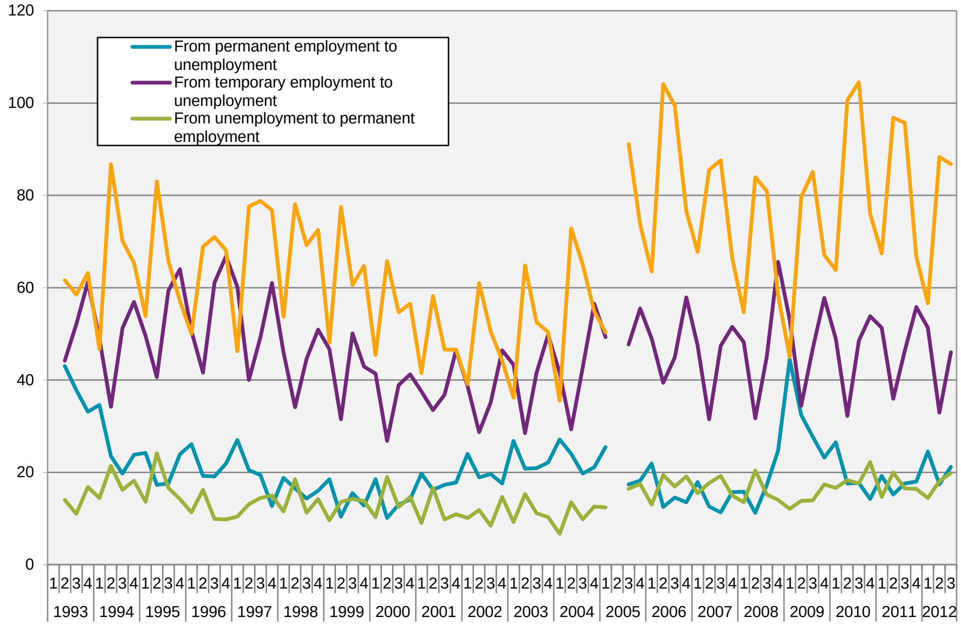
Variable	**Explanation**
Employed	The number of people who worked at least one hour during the reference week or who were temporarily absent from a job.
Unemployed	The number of persons who were without work during the reference week, but who sought employment in the past four weeks. Also included here are persons who have obtained employment that will begin within three months.
Fafraa	Flow from the unemployed to the permanent employed between two quarters or alternatively between two months.
Tafraa	Flow from unemployed to temporary employed between two quarters or alternatively between two months.
Afrafa	Flow from full-time to unemployed between two quarters or alternatively between two months.
Afrata	Flow from temporary workers to unemployed between two quarters or alternatively between two months.
Ttfafraa	Flow from unemployed to the number of hours permanently employed between the two quarters or alternatively between two months.
Tttafrafa	Number of people who change status from unemployed to hours of temporary employees between the two quarters or alternatively between two months.

The aim concerning data has been to obtain comparable time series from 1993. However, variable properties such as definition details, measurement methods and estimation methods have varied over the years. In 1993, a new estimation method was introduced including an improved non-response adjustment, as well as a new system for the distribution of the measurement weeks. In April 2005 revisions due to a recent EU-regulation were implemented. These revisions resulted in time series breaks over which the gross flows cannot be estimated since individuals were not reappearing after the change.

The target populations for this study are individuals aged 16-24 and 16-64 respectively. Primarily, we have worked with data adjusted and linked due to the changes in the survey, but not data that are seasonally adjusted. We have instead chosen to take account of seasonal variations in the statistical analysis. Flow data after the major change in 2005 are obtained from the published time series, while previous flows are obtained somewhat approximately based on the annual cross-sectional weights of the survey. These flow weights are not calibrated to population totals to the same extent as those for the published flows.

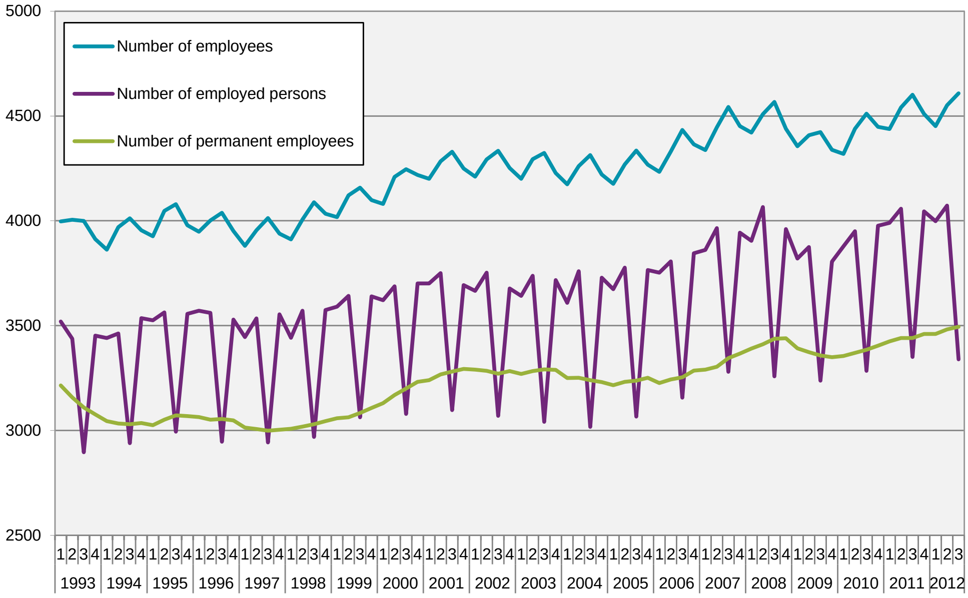
Below is the graph of the number of persons employed, in work and in permanent employment (total), as well as curves showing the development of flows in the labour market. This provides a picture of the long-term development since 1993.

Figure 3.1
LFS time series variables (flow statistics), measured in the thousands (age 16-64).



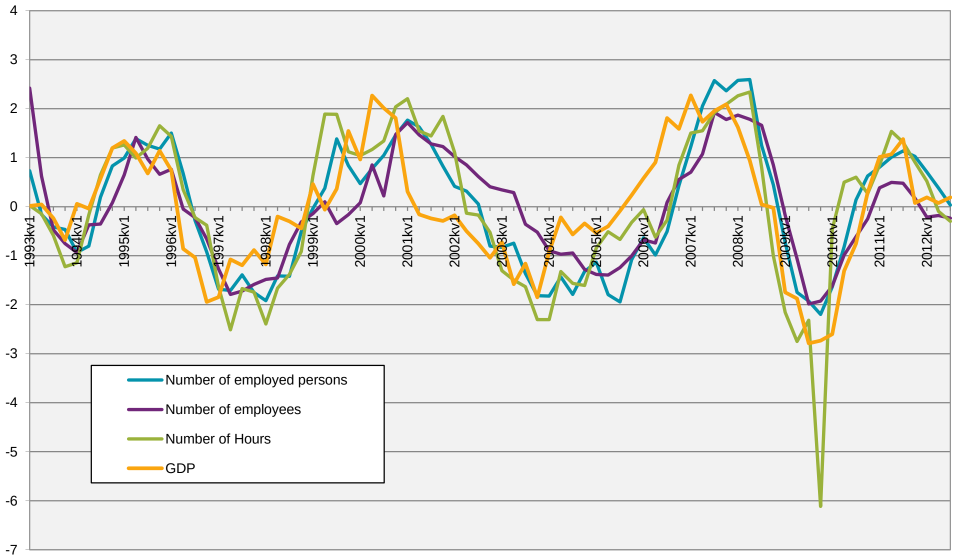
Source: LFS, Statistics Sweden

Figure 3.2
LFS time series variables (stocks), measured in thousands (age 16-64).



Source: LFS, Statistics Sweden

Figure 3.3
LFS time series variables (flow statistics), measured in the thousands (age 16-64).



Source: LFS, Statistics Sweden
Comment: see the annex for gap definition

Figures 3.1-3.3 illustrate the development of some key variables that reflect developments in the labour market. The flow indicators in Figure 3.1 show a highly seasonal pattern. The largest amplitudes are obtained for the series "to temporary employment from unemployment", second is the opposite flow "from temporary employment to unemployment". The trends for the flows to and from temporary employment are higher than the corresponding trends for the flows to and from "permanent employment from unemployment". Business cycle changes affected the level of temporary employment to a greater extent than the level of permanent employment. This is also indicated by Figure 3.2 where those in work vary considerably more according to season than those in permanent employment.

So-called gaps are calculated to indicate how the labour market variables relate to the boom and recession phases of the economy (see the annex for details). Positive values indicate a boom period and negative values a period of recession (Fregert and Jonung 2005). The development of all variables associated over time, but the development of hours worked precedes the development of employment which was expected from the above illustrations. The GDP has been included in Figure 3.3 in order to show how the labour market relates to the production side of the economy. It is evident that a change of the GDP gap precedes a change in the employment gap but not in the gap for the number of hours worked.

4. Models of Analysis

In this part of the analysis we will compare different time series more in detail. The procedure follows a standard time-series analysis, as we attempt to identify the different components of a series in order to describe the cyclical component which we are particularly interested in. The cyclical component here will denote the partly irregular fluctuations that are neither seasonal nor random or belonging to a trend. The analysis is based on the assumption that the development over time of a variable can be described by such non-observable components.

A general and flexible tool for this analysis is known as the UCM approach (*Unobserved Components Modelling*). Here a number of components are specified as well as their characteristics. Main components are trends, cycles, seasons and an irregular or random component. Model specification determines characteristics of the components, which may be either fixed or stochastic, according to detailed specifications if required. There are also a number of indicators proposed on how the model works.

It is possible to specify parameters for changed settings or interventions such as revisions of variables or in survey design. In this case we use, when possible, the published series adjusted for various changes in the variables. For change in the LFS 2005 however, intervention parameters are added accounting for possible level differences and for the lack of bridging flows.

In addition to UCM models we then examine correlations between changes in employment levels and in flows. There are many approaches to analyse time series, and the approach applied in this section is derived from the methods of Box and Jenkins. The method is better known under the name of ARIMA (Auto Regressive Integrated Moving Average). This method is based on stationary series; see the annex for a discussion on stationarity, and generally Box and Jenkins (1976). Given that the conditions of stationarity are met, different ARIMA models are estimated. Model specification is examined with the help of the resulting autocorrelation and partial autocorrelation functions. The properties of a model are tested further using various diagnostic tests to evaluate whether the estimated error term meets the condition of white noise. If tests indicate that the error term is different from white noise the model has to be modified and a new model specification is tested.

The analysis is then extended to take account of possible linear dependencies between the flow variables; this is done most easily in the context of a Vector Auto Regressive (VAR) approach. A test is also made here for stationarity of the different variables precedes model specification. Different flow indicators in a regression may jointly explain each other with time lags. Consequently, tests for lag structure (Information criteria) and also for parameter stability are essential for VAR models. In the resulting VAR model, changes will then be explained by the historical values of the dependent variable as well as the historical development of the explanatory variables.

Unlike classical regression modelling, neither ARIMA- nor VAR-modelling departs from economic analysis. The idea of the models is instead that the forecasts can be explained by both the historical development and by exogenous shocks. The traditional models assume that general equilibrium is prevailing in the economy, and thus is unsuitable for time series analyses of periods of dramatic changes in the business cycle.

The idea of the different approaches with UCM, ARIMA and VAR is to test the responsiveness of various flow indicators and labour market aggregates from three different perspectives. The UCM models are intended to answer the question of adherence from a graphical perspective, the ARIMA models are intended to explain the relationship between flow indicators and level changes on the labour market in the short run, while the VAR approach is intended to measure the association between different trends in the long run. In this way, it is possible to obtain a comprehensive picture where the connection between the short and long time series perspectives is clarified.

Analyses of this kind are not independent of the methods used. Different methods of analysis may provide different results; see for example Canova (1998). The results therefore must be interpreted with care. In addition, the LFS is a sample survey and data are therefore affected by sampling as well as measurement errors.

5. Analysis and Results

5.1 The Component Model

In several of the figures the results from the UCM approach are shown through the series resulting after the removal of the trend and seasonal components. Remaining are cyclical components including random or irregular factors, referred to as cycles. After smoothing through local regression ("loess", a non-parametric approach) the cycles are shown in the figures. The vertical lines signify business cycle phases, according to an analysis of the gross national product (GDP) of Bergman (2011), see also SCB (2012). The bold vertical lines indicate the beginning of the downturns while the corresponding thin lines mark the completion of those stages.

The results are based on the quarterly flows for those aged 16-64. Cycles calculated from gross flows between temporary employment and unemployment are shown, as well as series calculated from unemployment and employment levels. The original series have been transformed to logarithms, which are beneficial for both the graphical presentation and the interpretation.

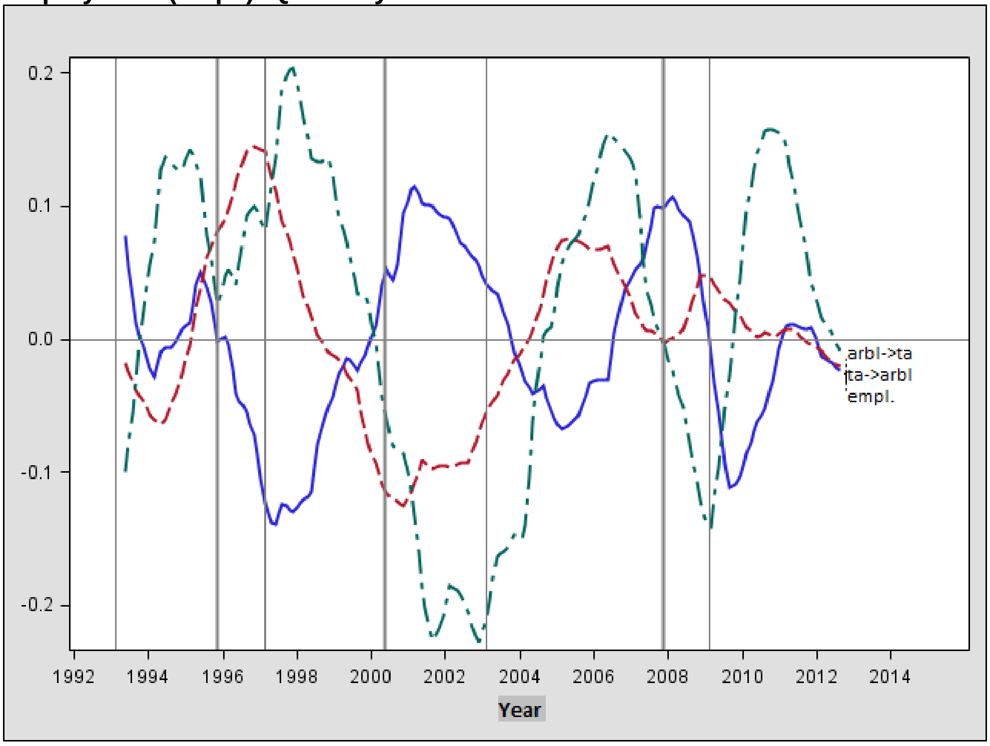
Figure 5.1 compares the UCM cycles for flows between unemployment and temporary employment as well as for the level of employment (number of persons employed). It looks as if the flow curves (the dashed lines) turn at least 3-4 quarters earlier than the curve for employed persons (the solid line). For example the curve turns downwards in the middle of 1995 for the employed (the solid blue line). The curve for the transition from temporary employment to unemployment (ta-> arbl, red line) turns upwards one quarter into 1994, while the curve of the flow from unemployment to temporary employment (arbl-> take, green line) starts to turn some quarters into 1994. For the period from 1998 to 2008, the differences between the curves are larger; here it looks as if the flows turn at least 7-8 quarters earlier than employment.

The differences are similar in figure 5.2 where cycles for flows between unemployment and temporary employment are compared to cycles for the unemployed. Flow curves are at least 3-4 quarters earlier than the curve for the unemployment level; for the period 1998-2008 the differences are about the double.

The analysis underlying the figures 5.1 and 5.2 is based on quarterly data for all those aged 16-64. Estimates of monthly data for all aged 16-64, as well as quarterly data for those aged 16-24 give approximately the same conclusions. Analysis of monthly data for those aged 16-24 and analysis of flows between employment and unemployment are more uncertain.

Figure 5.1

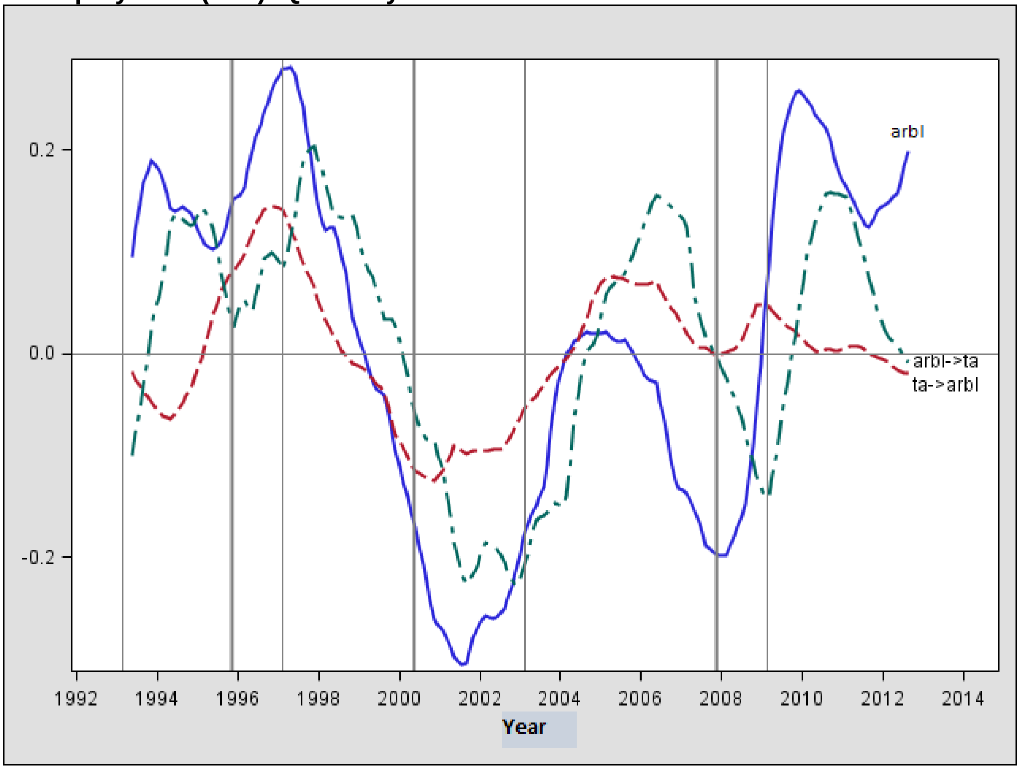
Time series according to the UCM model (16-64). Flows from unemployment to temporary employment (arbl−>ta) and vice versa (ta−>arbl). Level of employment (empl.). Quarterly data.



Note: The values for the level of employment are multiplied by 5 in order to give clearer comparisons. Curves smoothed by loess (local regression)

Figure 5.2

Time series according to the UCM model (16-64). Flows from unemployment to temporary employment (arbl−>ta) and vice versa (ta−>arbl). Level of unemployment (arbl). Quarterly data.



Note: Curves smoothed by loess (local regression).

5.2 The ARIMA models

Tables 5.1 and 5.2 show the estimates from the models that, based on statistical tests, appeared superior. It should be pointed out that the ARIMA models have not been adjusted with regard to possible extreme values. The motivation is a fear of losing important information that may exist in the series and important analysing the relationships. All models have undergone diagnostic tests. The input variables have been tested for stationarity through the Dickey-Fuller test, and the error terms have finally been tested for white noise. The models may be further improved by modelling the error terms more in detail. Heteroskedasticity is often a potential problem but statistical tests indicate that this is of minor importance here, with the exception of a few cases only.

Table 5.1
Effects of flows between unemployment and temporary employment on employment and unemployment growth. Cohort aged 16-24, quarterly data.

	Δlog(A)	Δlog(S)	Δlog(A)	Δlog(S)	Δlog(A)	Δlog(S)	Δlog(A)	Δlog(S)	Δlog(A)	Δlog(S)
log(afrata)(q-0)	0.111***	-0.018***								
	[0.025]	[0.003]								
log(tafraa)(q-0)	-0.176***	0.016***								
	[0.023]	[0.003]								
log(afrata)(q-1)			0.058**	-0.011***						
			[0.025]	[0.003]						
log(tafraa)(q-1)			-0.079**	0.003						
			[0.033]	[0.004]						
log(afrata)(q-2)					0.014	-0.006*				
					[0.026]	[0.003]				
log(tafraa)(q-2)					-0.064**	-0.001				
					[0.03]	[0.003]				
log(afrata)(q-3)							-0.009	-0.002		
							[0.025]	[0.003]		
log(tafraa)(q-3)							0.031	-0.001		
							[0.03]	[0.003]		
log(afrata)(q-4)									-0.020	-0.004
									[0.025]	[0.003]
log(tafraa)(q-4)									-0.063**	0.009***
									[0.029]	[0.003]
Intervent	0.079***	-0.003	0.046**	0.002	0.051**	0.003	0.015	0.002	0.060***	-0.003
	[0.018]	[0.002]	[0.023]	[0.002]	[0.022]	[0.002]	[0.021]	[0.002]	[0.02]	[0.002]
Constant	0.254***	-0.003	0.138	0.017	0.251**	0.009	0.014	0	0.304***	-0.020*
	[0.085]	[0.01]	[0.118]	[0.013]	[0.119]	[0.014]	[0.108]	[0.012]	[0.097]	[0.011]
Quarterly effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit	0.92	0.96	0.88	0.95	0.90	0.94	0.89	0.94	0.90	0.95
Observations	63	63	63	63	62	62	61	61	60	60

Note: standard errors in parentheses * $p < 0.10$, * * $p < 0.05$, * * * $p < 0.01$. (q-i) represents quarters. The designation Δlog(A) refer to the percentage change in the number of persons unemployed, and Δlog(S) percentage change in the number of person employed.

The results of the regressions for the population group aged 16-24 reveal several empirical correlations. To test the robustness of the analysis, two dependent variables were used: change in the number of employed persons Δlog(S) and change in the number of persons unemployed Δlog(A). All input variables are converted to logarithms to simplify interpretation of the regression estimates. Table 5.1 indicates that the flow to unemployment from temporary employment and the change in number of persons unemployed form a positive association lagged up to one quarter. An interpretation of the estimated coefficient 0.058 is that, all things being equal, the number of unemployed can be expected to increase by an average of 5.8 percent when the flow to unemployment increases by one percent, but only after one quarter. The effect is statistically significant at the 5-percent level. Also verified is a negative association between the flow from temporary employment to unemployment and the change of number of persons employed with a lag of two quarters.

No similar discernible correlation exists between the flow to temporary contracts log (tafraa) and the change in the number of persons employed Δlog(S). However, there are indications that the inflow to temporary contracts has a slightly negative effect on the change in the number of persons unemployed after up to four quarters. The corresponding flow has a positive effect on the change of number of persons employed during the current quarter and even after up to four quarters. There is an interesting difference in the way that the flow variables affect the change in the number of unemployed persons and in the number of employed persons. For example, the effect of an increase in the flow of temporary workers on employment growth is slightly delayed. In other words, it seems that recruitments are affected later than the lay-offs among young people.

Table 5.2
Effects of flows between unemployment and temporary employment on employment and unemployment growth. Individuals aged 16-64, quarterly data.

	Δlog(A)	Δlog(S)	Δlog(A)	Δlog(S)	Δlog(A)	Δlog(S)	Δlog(A)	Δlog(S)	Δlog(A)	Δlog(S)
log(afrata)(q-0)	0.185***	-0.027***								
	[0.032]	[0.004]								
log(tafraa)(q-0)	-0.256***	0.027***								
	[0.027]	[0.003]								
log(afrata)(q-1)			0.125***	-0.019***						
			[0.033]	[0.004]						
log(tafraa)(q-1)			-0.208***	0.020***						
			[0.033]	[0.004]						
log(afrata)(q-2)					0.032	-0.013***				
					[0.037]	[0.005]				
log(tafraa)(q-2)					-0.142***	0.018***				
					[0.035]	[0.004]				
log(afrata)(q-3)							-0.025	-0.001		
							[0.040]	[0.006]		
log(tafraa)(q-3)							0.000	0.005		
							[0.040]	[0.005]		
log(afrata)(q-4)									-0.039	-0.003
									[0.039]	[0.005]
log(tafraa)(q-4)									-0.098***	0.014***
									[0.038]	[0.004]
Intervent	0.068***	-0.005***	0.063***	-0.003**	0.052**	-0.003*	0.025	0.000	0.044***	-0.003**
	[0.011]	[0.001]	[0.012]	[0.002]	[0.014]	[0.002]	[0.016]	[0.002]	[0.014]	[0.002]
Constant	0.353***	-0.011	0.430**	-0.015	0.557**	-0.033	0.175	-0.027	0.609***	-0.051
	[0.133]	[0.017]	[0.149]	[0.022]	[0.185]	[0.023]	[0.207]	[0.028]	[0.180]	[0.026]
Quarterly effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit	0,93	0,97	0,90	0,94	0,91	0,94	0,89	0,94	0,90	0,94
Observations	63	65	63	65	62	64	61	63	60	62

Note: standard errors in parentheses * p < 0.10, * * p < 0,05, * * * p < 0.01. (q-i) represents quarters. The designation Δlog(A) refer to the percentage change in the number of persons unemployed, and Δlog(S) percentage change in the number of persons employed. Comment: see table 2.

Table 5.2 presents the results of ARIMA regressions for the 16-64 age group. There is a statistical correlation between the inflow to unemployment and the change in the number of persons employed as well as between the inflow to unemployment and the change in the number of unemployed. The findings for the younger group aged 16-24 also apply to the larger population group to some extent. For example, the lag is up to three months statistically confirmed for an increase in the number of persons unemployed when the flow to unemployment from temporary employment increases.

A corresponding time lag also applies to the changes in the number of persons employed but with the opposite sign. In the regression analyses, different control variables were included to account for quarterly effects and effects due to the redesign of the LFS in 2005. While the estimated regression coefficients thus are adjusted in order to incorporate the economy's cyclical phase and the redesign, they are not adjusted for any outliers and dependencies between different times. The effect of this has been analysed and possible adaptations of the error terms of the ARIMA models do not change the regression results presented in tables 5.1 and 5.2.

5.3 Prediction properties of the ARIMA models

In this section, we examine predictions from the ARIMA models. We will indicate if, and to what extent, flow variables improve prediction properties instantaneously or even when they are lagged a couple of quarters. If flow variables are indicators of employment trends, predictions will be improved with such variables included in the models.

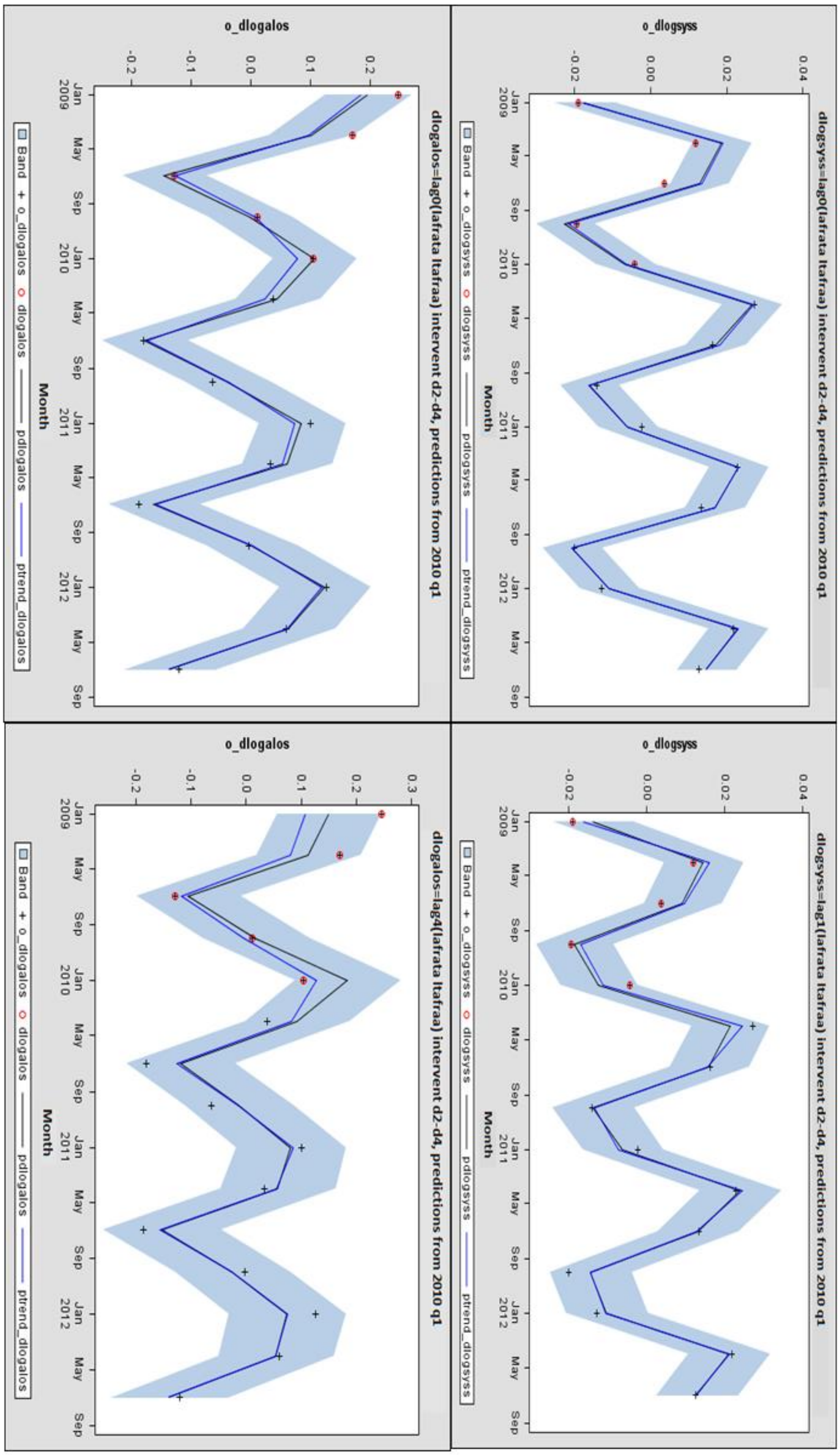
Different models are estimated for the tests with data up to a certain quarter. Thereafter, the parameter estimates are used for one or more projections for the coming quarters. These projections are compared with the observed values from the LFS for these quarters. Figure 5.3 shows predictions or projections over a longer period beginning in 2010 for some models with flow variables of different lags. The predictions are compared to the observed values of log changes in unemployment and employment. Other variables are seasonal dummies for each quarter (d2, d3 and d4), an intervention variable for the EU adaptation of the LFS in 2005 and flows between temporary employment and unemployment. The flows are of different lags in accordance with the previous section. Cross-correlations between the flows to and from unemployment respectively may affect coefficient estimates and standard errors. For predictions however, this is of minor importance.

In the figures observed, values are indicated with +, highlighted in red for the estimation period which, however, only is shown for 2009 and onwards despite previous quarters were used. The solid lines are connecting model-generated values, that is, the predictions (pdlogsyss, pdlogalos). The shaded areas indicate the corresponding prediction intervals on the 95-percent level. The thinner lines finally show predictions without regard to the error term structure with 4 to 6 auto-regressive terms.

We find that the models fairly well replicate and predict the observed values; the periods before and after the turn of the year 2009/ 2010. Model versions of zero-lagged flows seem to be superior; the examples with lags one quarter for dlogsyss (employed) or with four quarters for dlogalos (unemployed) give inferior predictions.

Figure 5.3

Predictions and observed values of the changes in employment (dlogsyss) and unemployment (dlogalos) when flows between unemployed and temporary employees are of different lags. ɵ (+) for the observed values in the estimation period (prediction period). Predictions and prediction intervals are linked.



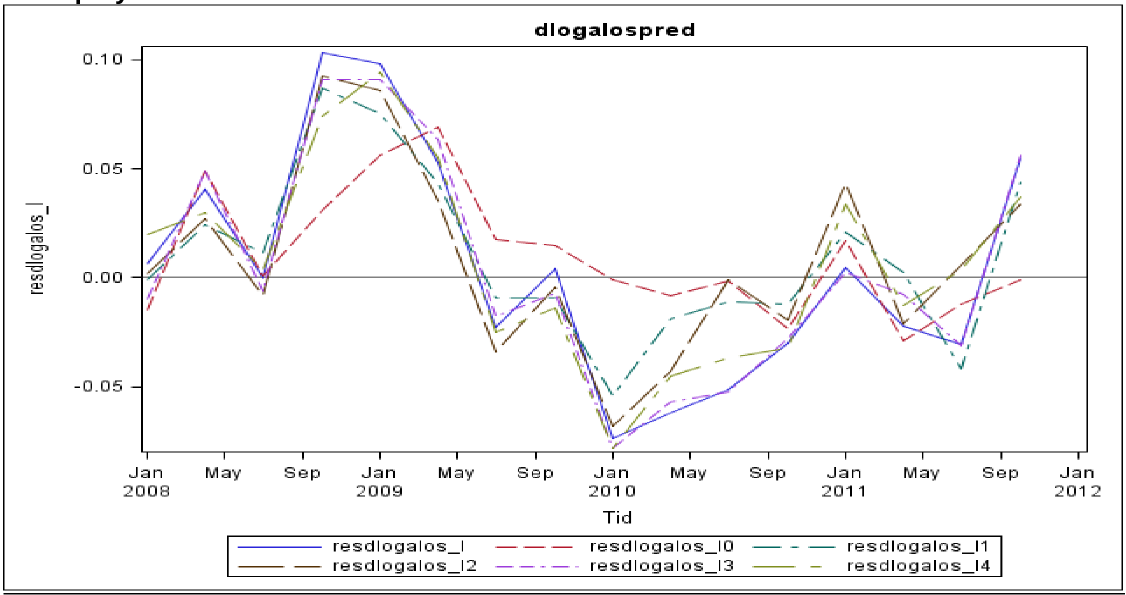
In more extensive tests, different models are estimated using time series data up to a certain point, say first quarter 2009. Thereafter, parameter estimates are used for projections for the next quarter, second quarter 2009. The prediction is compared to the results for this quarter so that the prediction error can be calculated. The procedure is repeated with the estimation period successively extended one quarter and again a projection for the following quarter and a comparison to the observed value of the LFS is made. The estimated models correspond to those of the previous section; on the one hand a basic model without flow variables and on the other hand models with flow variables from previous quarters differently lagged. As before, it is the changes in the number of persons employed or unemployed which alternate as the dependent variable. An auto-regressive structure is specified for the error term, according to the previous section. Independent variables are seasonal dummies, a dummy variable for the period after 2005 and flows between unemployment and temporary employment.

Figures 5.4 and 5.5 show the prediction errors a quarter ahead for the log quarterly changes in the number of persons employed and unemployed. It is obvious that the red dotted lines diverge from the others, also from the solid lines. The latter denote models without flow variables, while the red dashed line is based on models with flow variables added and observed as late as possible, that is, without lag. It seems as if the current flow observations usually reduce prediction error, while previous observations of the flows have little or no effect, according to the other lines. The equivalent applies for observations of even earlier flows (not shown).

Of particular interest are the turning points. One turning point of the number persons employed and unemployed is just before or around the turn of the year 2009/ 2010 according to the UCM analysis in figures 5.1 and 5.2. For this change the predictions are good for models with current flows according to figures 5.4 and 5.5. For the end of 2008 and start of 2009 with a sharp change in employment and unemployment are all predictions found to be bad.

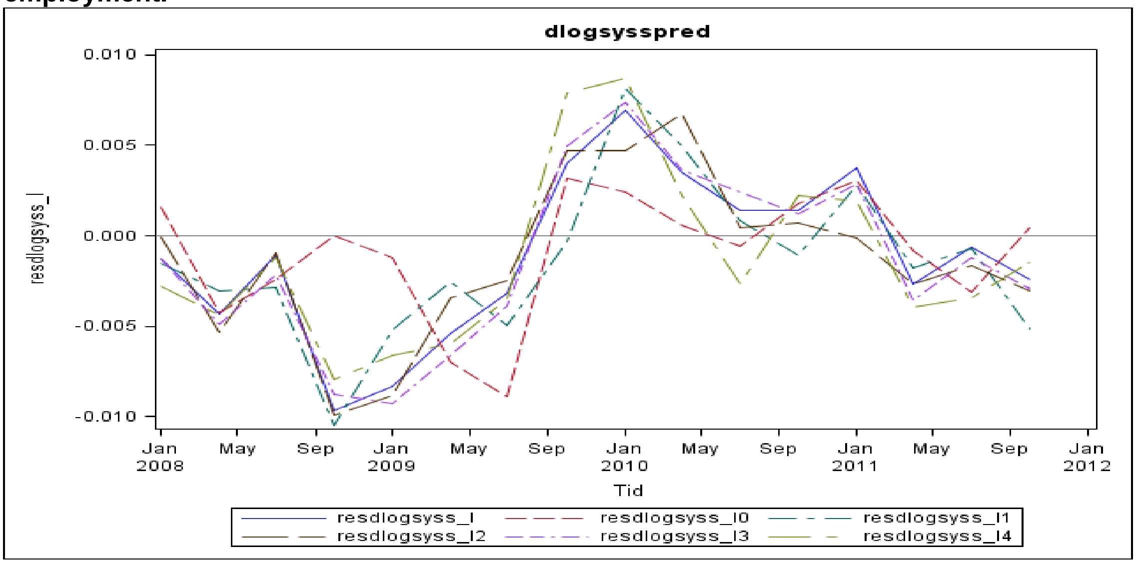
For models based on monthly flows, unstable results are obtained; monthly data is therefore probably insufficient for inference.

Figure 5.4
Errors of predictions for projections one quarter ahead of the change in unemployment.



Note: The estimation period is gradually extended a quarter. Models without and with flow variables of different lags. resdlogalos_l specifies the error when flows not are included, resdlogalos_ ln the errors when flow variables are lagged n quarters (n =0, 1, 2, 3, 4). The values are allocated to the first day of the quarter.

Figure 5.5
Errors of predictions for projections one quarter ahead of the change in employment.



Note: The estimation period is gradually extended a quarter. Models without and with flow variables of different lags. resdlogsyss_l specifies the error when flows not are included, resdlogsyss_ln the errors when flow variables are lagged n quarters (n =0, 1, 2, 3, 4). The values are allocated to the first day of the quarter.

5.4 Vector autoregressive models (VAR)

In the previous regression analyses, the association between the change in the number of persons employed and the flows into unemployment from permanent employment and into unemployment from temporary employment were examined. The explanatory variables were lagged some quarters in order to show how an increase in a flow affects in the number of persons employed and unemployed from one quarter to another. This section is not about studying the change between quarters, but instead links between different trends are analysed. The latter are preferably measured through so-called gaps (see the annex for a technical description), where the percentage deviation from the long-term trend is calculated for all input variables. The analysis therefore deals with the relationships between different flow-gaps through a multivariate regression analysis. An example of this type of analysis is provided by Chen and Mills (2009) in an article about the relationship between growths in different countries. To simplify the interpretation of the VAR-models, impulse-response functions are estimated. Impulse-response functions describe how a given shock in the equation system affect the target variable a few quarters ahead, all things being equal. For a technical description of the impulse-response models, see Hamilton (1994).

Figure 5.6
Impulse-response model for the employment gap, individuals 16-24 years.

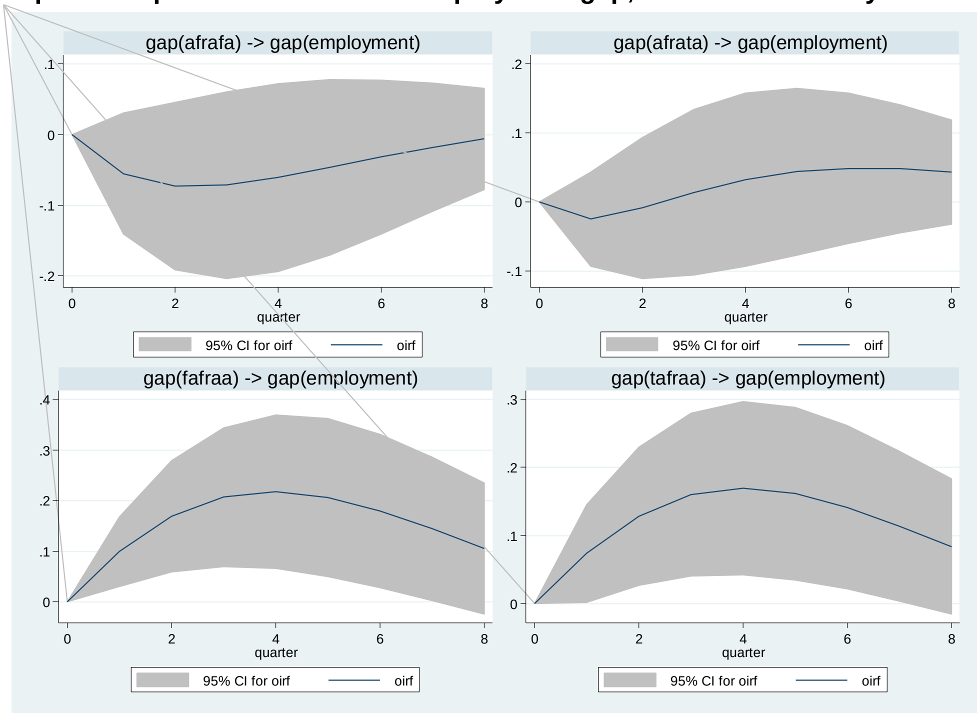
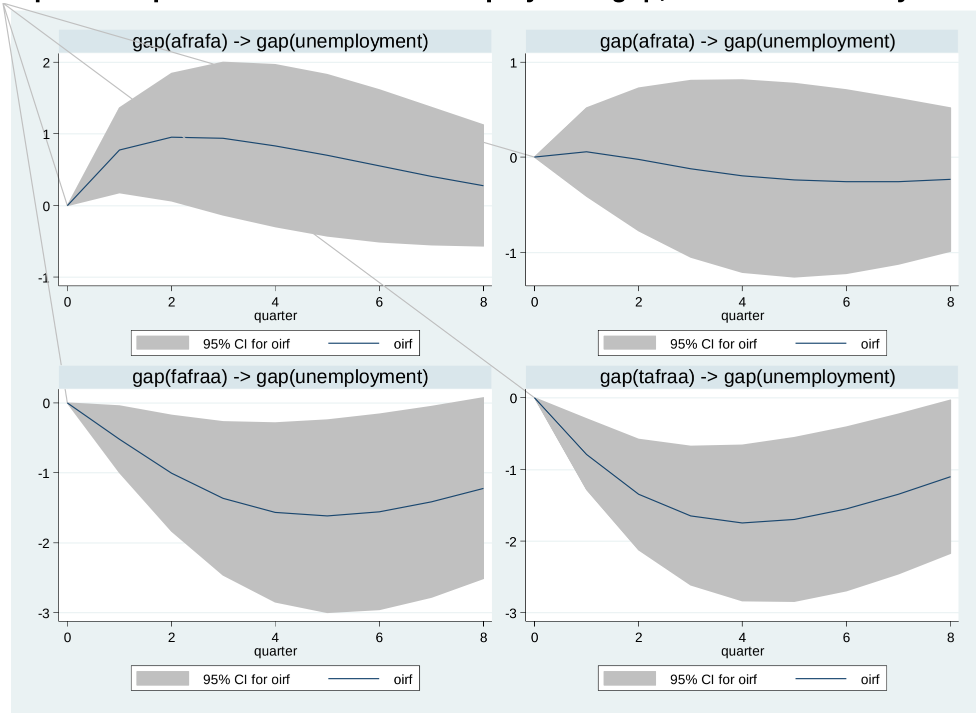


Figure 5.7
Impulse-response model for the unemployment gap, individuals 16-24 years.



Shocks or instabilities in the flows to unemployment from permanent employment and to unemployment from temporary employment have no verified effect on the future employment gap. However, there is some indication that the shocks in the flow gaps to permanent employment and temporary employment from unemployment increases the employment gap. The employment gap increases up to the fourth quarter after a shock has occurred in the flow to temporary employment. After four quarters the effect of the shock of the employment gap declines. Corresponding trends are also indicated for the change in the number of unemployed. Shocks in the flows to permanent employment and to temporary employment have a negative effect on the unemployment gap. After about 7-8 quarters the unemployment gap are no longer significant and returns to normal trend levels.

Figure 5.8
Impulse-response model for the employment gap; all, aged 16-64.

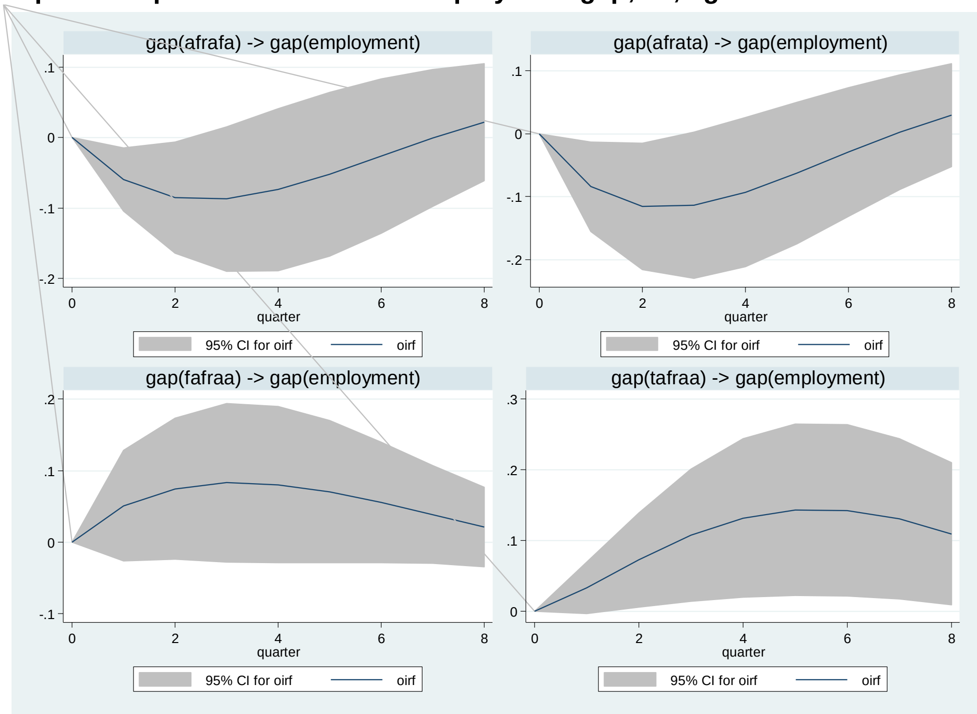
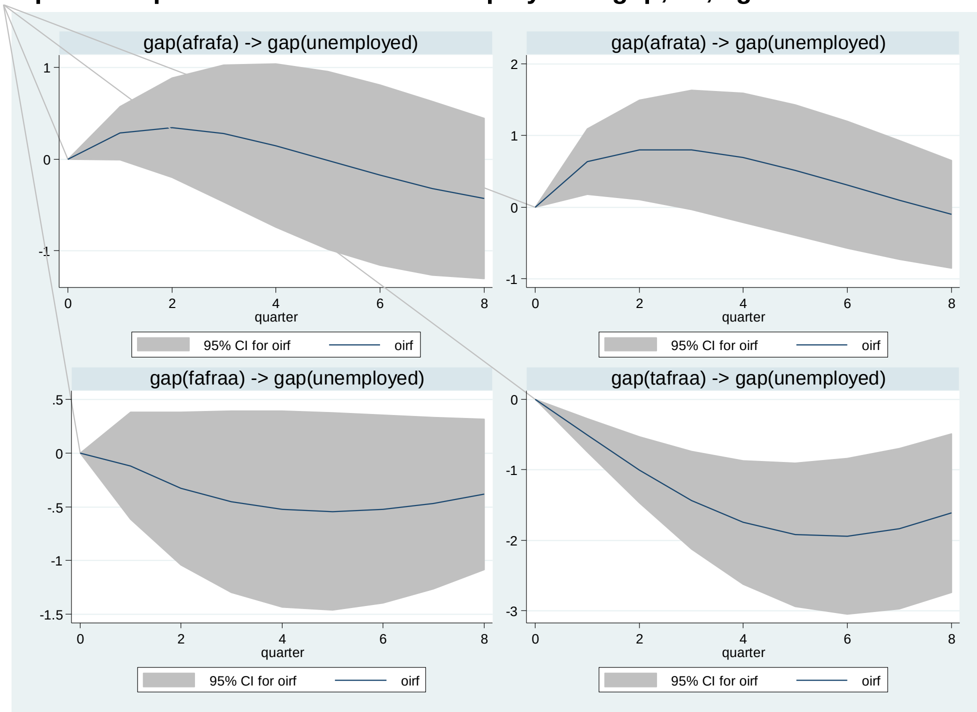


Figure 5.9
Impulse-response model for the unemployment gap; all, aged 16-64.



The discussed trends for those aged 16-24 are also observed for the larger population group aged 16-64. As shown in Figure 5.8, three out of four different labour market shocks have a statistically significant effect on future employment gaps. Shocks in the flow gap variable "fafraa" do not have a significant effect on the future employment gap. A comparison of Figure 5.6 and 5.8 indicates, to some extent, that the various shocks in the labour market flattens out slightly later in age group 16-64 as compared to the younger cohorts. A similar pattern also appears if we compare the unemployment gaps in figure 5.7 and 5.9.

As a further step in the analysis have tests been made to evaluate if variables included in the VAR models form a long-term equilibrium, i.e. if the employment gap follows the same long-term trend as the flow gaps. However, no empirical support was found, neither for those aged 16-24 nor for the entire population of aged 16-64.

6. References

Bergman, M (2011). *Tidsbestämning av svensk konjunktur 1970 – 2010.* Rapport 2011/ 2, Finanspolitiska rådet.

Box, G.E.P, and Jenkins, G.M. (1976), *Time Series Analysis: Forecasting and Control*, revised edition, San Francisco, Holden-Day.

Canova, F. (1998). *Detrending and business cycle facts*. Journal of Monetary Economics, 41 (3) (1998), pp. 475–512.

Chen, X. and Mills, T.C. (2009). *Evaluating growth cycle synchronisation in the EU*. Economic Modelling, 26 (2). pp. 342-351.

Ebrahimy, E. and Shimer, R. (2010*), Stock-flow matching*. Journal of Economic Theory, 145, 1325-1353.

Enders, W. (1995), *Applied Econometric Time Series*, New York, John Wiley & Sons.

Jonung, Fregert, K & L (2005). *Makroekonomi*. Studentlitteratur.

Gustafson, C-H & Hagsten, E (2005). *Produktion och sysselsättning i ekonomins olika faser*. Fokus på arbetsmarknad och utbildning, IAM 2005:2, Statistics Sweden.

Hamilton,J. H. (1994). *Time series analysis*. Princeton University Press, Princeton, New Jersey.

SCB (2012). *Employment and hours worked in the business process*. Statistical reports, AM110SM1201, Statistics Sweden.

Shimer, R (2012). *Reassessing the ins and outs of unemployment*. Review of Economic Dynamics 15, 127-148.

7. Annex

7.1 Definitions

The gap for an arbitrary variable x is calculated as follows:

$$gap(x_t) = \frac{(season(x_t) - trend(x_t))}{trend(x_t)}$$

where season denotes seasonally adjusted values and trend represents the long-term stochastic trend. The long-term trend has been calculated by the so-called Hodrick-Prescott filter. Seasonal adjustment is made using the TramoSeats application in the Demetra package (version 1.0.2).

7.2 Conditions for stationarity

Fundamental for ARIMA modelling are requirements of weak stationarity. This means that the underlying probability distribution does not change over time. A definition of weak stationarity is:

1. The mean value is constant, i.e. $E(y_t) = \mu$
2. The covariance between y_t and y_s only depends on time difference t-s.
3. The variance is constant, i.e.; $E(y_t - \mu)^2 = \sigma^2$

A common method to check if a time series is stationary is by using time series charts. Other more formal methods are based on the autocorrelation function (ACF), the partial autocorrelation function (PACF) and the Dickey-Fuller test. For a more detailed description of the properties of different stationarity tests the reader is referred to (Enders 1995, p. 68), among others.

7.3 Regression tables

Table 7.1
The VAR model; population 16 to 24 years quarterly data.

	gap(syss)	gap(afrafa)	gap(afrata)	gap(fafraa)	gap(tafraa)
gap(syss)(q-1)	0.876***	4.928	2.030	-1.616	-3.187***
	[0.04]	[3.30]	[1.46]	[1.59]	[0.98]
gap(afrafa)(q-1)	-0.027*	0.219*	0.0711	-0.0502	-0.0208
	[0.00]	[0.12]	[0.05]	[0.06]	[0.03]
gap(afrata)(q-1)	-0.0048*	0.138	0.241***	-0.0513	0.0671
	[0.00]	[0.20]	[0.09]	[0.09]	[0.06]
gap(fafraa)(q-1)	0.0081***	-0.148	-0.0362	0.603***	0.128**
	[0.00]	[0.19]	[0.08]	[0.09]	[0.06]
gap(tafraa)(q-1)	0.0095**	-0.888**	0.166	0.357**	0.393***
	[0.00]	[0.37]	[0.16]	[0.18]	[0.11]
Intervention	-0.0179	8.305	-1.722	-1.252	3.067
	[0.09]	[7.15]	[3.18]	[3.45]	[2.13]
Constant	0.0168	-2.353	1.700	1.574	-0.982
	[0.09]	[7.12]	[3.16]	[3.44]	[2.12]
Quarterly Effects	Yes	Yes	Yes	Yes	Yes
Observations			77		
AIC (model selection)			18.8		
Fit	0.89	0.26	0.19	0.19	0.44

Comment: Standard errors in brackets[]. * * *, * *, * indicate significance at the 1, 5 and 10 percent level, respectively. The index in parenthesis() show lag length where q denotes quarter. Gap = ((seasonally adjusted (x) – stochastic trend (x))/stochastic trend (x))

Table 7.2
The VAR model; population 16 to 24 years quarterly data.

	gap(arbl)	gap(afrafa)	gap(afrata)	gap(fafraa)	gap(tafraa)
gap(arbl)(q-1)	0.915***	-0.496	-0.0456	0.0719	0.323***
	[0.03]	[. 38]	[0.17]	[0.18]	[0.11]
gap(afrafa)(q-1)	0.0303***	0.218*	0.0674	-0.0479	-0.0199
	[0.01]	[0.12]	[0.05]	[0.06]	[0.04]
gap(afrata)(q-1)	0.0218	0.172	0.257***	-0.0637	0.0453
	[0.02]	[0.19]	[0.09]	[0.09]	[0.06]
gap(fafraa)(q-1)	-0.0400**	-0.141	-0.0120	0.589***	0.124**
	[0.02]	[0.19]	[0.09]	[0.09]	[0.06]
gap(tafraa)(q-1)	-0.101***	-0.911**	0.135	0.377**	0.408***
	[0.03]	[0.37]	[0.16]	[0.18]	[0.11]
Intervention	-0.0179	8.931	-1.498	-1.439	2.663
	[0.61]	[7.17]	[3.22]	[3.47]	[2.16]
Constant	-0.112	-2.871	1.544	1.712	-0.646
	[0.61]	[7.15]	[3.21]	[3.46]	[2.15]
Quarterly Effects	Yes	Yes	Yes	Yes	Yes
Observations			77		
AIC (model selection)			22.8		
Fit	0.94	0.26	0.17	0.54	0.42

Comment: see table 7.1.

Table 7.3
The VAR model; population 16 to 64 years quarterly data.

	gap(syss)	gap(afrafa)	gap(afrata)	gap(fafraa)	gap(tafraa)
gap(syss)(q-1)	0.863***	1.466	0.240	0.537	-2.227***
	[0.05]	[1.64]	[1.12]	[1.92]	[0.42]
gap(afrafa)(q-1)	-0.0049**	0.651***	-0.0203	0.0272	0.0430**
	[0.00]	[0.06]	[0.04]	[0.07]	[0.02]
gap(afrata)(q-1)	-0.0151***	0.507***	0.265**	-0.538***	0.0391
	[0.01]	[0.17]	[0.12]	[0.20]	[0.04]
gap(fafraa)(q-1)	0.0041	0.0424	-0.136*	0.0798	0.0221
	[0.00]	[0.10]	[0.07]	[0.12]	[0.03]
gap(tafraa)(q-1)	0.0125*	-0.819***	0.127	0.915***	0.860***
	[0.01]	[0.22]	[0.15]	[0.25]	[0.06]
Intervention	0.0396	6.097**	0.806	-1.510	-0.0816
	[0.09]	[2.86]	[1.96]	[3.35]	[0.74]
Constant	-0.0383	-4.081	-0.543	0.567	.380
	[0.09]	[2.74]	[1.88]	[3.21]	[0.71]
Quarterly Effects	Yes	Yes	Yes	Yes	Yes
Observations			77		
AIC (model selection)			13.1		
Fit	0.90	0.84	0.14	0.40	0.92

Comment: see table 7.1.

Table 7.4
The VAR model; population 16 to 64 years quarterly data.

	gap(arbl)	gap(afrafa)	gap(afrata)	gap(fafraa)	gap(tafraa)
gap(arbl)(q-1)	0.934***	-0.207	0.224*	-0.187	0.240***
	[0.04]	[0.19]	[0.13]	[0.23]	[0.05]
gap(afrafa)(q-1)	0.0243*	0.660***	-0.0644	0.0502	0.0425**
	[0.01]	[0.07]	[0.04]	[0.08]	[0.02]
gap(afrata)(q-1)	0.101***	0.539***	0.198	-0.495**	0.0119
	[0.03]	[0.18]	[0.12]	[0.21]	[0.05]
gap(fafraa)(q-1)	-0.00568	0.0387	-0.104	0.0647	0.0185
	[0.02]	[0.10]	[0.07]	[0.12]	[0.03]
gap(tafraa)(q-1)	-0.187***	-0.803***	-0.0418	0.995***	0.886***
	[0.04]	[0.21]	[14]	[0.25]	[0.06]
Intervention	-0.0103	6.107**	1.701	-1.892	-.357
	[0.56]	[2.81]	[1.89]	[3.29]	[0.75]
Constant	0.0555	-4.135	-0.935	0.713	0.573
	[0.54]	[2.72]	[1.83]	[3.18]	[0.73]
Quarterly Effects	Yes	Yes	Yes	Yes	Yes
Observations			77		
AIC (model selection)			16.7		
Fit	0.95	0.84	0.18	0.40	0.92

Comment: see table 7.1.

Table 7.5
The VAR model; population 16 to 24 years quarterly data.

	gap(syss)	gap(ttfafraa)	gap(tttafraa)
gap(syss)(q-1)	0.800***	1.136	-1.248***
	[0.06]	[0.84]	[0.40]
gap(ttfafraa)(q-1)	0.0212**	.0333	0.170***
	[0.01]	[0.12]	[0.06]
gap(tttafraa)(q-1)	0.0327**	0.485**	0.386***
	[0.02]	[0.21]	[0.10]
Intervention	-0.213	3.283	2.365
	[0.42]	[5.93]	[2.84]
Constant	0.121	-0.239	-0.713
	[0.42]	[5.95]	[2.84]
Quarterly Effects	Yes	Yes	Yes
Observations		77	
AIC (model selection)		12.0	
Legend Level	0.78	0.13	0.35

Comment: see table 7.1.

Table 7.6
The VAR model; population 16 to 24 years quarterly data.

	gap(arbl)	gap(ttfafraa)	gap(tttafraa)
gap(arbl)(q-1)	0.924***	-0.473	0.411***
	[0.04]	[0.32]	[0.15]
gap(ttfafraa)(q-1)	-0.0110	0.0312	0.160***
	[0.01]	[0.12]	[0.06]
gap(tttafraa)(q-1)	-0.122***	0.506**	0.364***
	[0.02]	[0.21]	[0.10]
Intervention	-0.0558	2.759	3.046
	[0.68]	[5.88]	[2.87]
Constant	-0.0322	-0.499	-0.500
	[0.68]	[5.93]	[2.89]
Quarterly Effects	Yes	Yes	Yes
Observations		77	
AIC (model selection)		12.9	
Fit	0.92	0.13	0.33

Comment: see table 7.1.

Table 7.7
The VAR model; population 16 to 64 years quarterly data.

	gap(syss)	gap(ttfafraa)	gap(tttafraa)
gap(syss)(q-1)	0.924***	0.135	-4.302***
	[0.05]	[1.88]	[0.80]
gap(ttfafraa)(q-1)	0.00666**	0.0746	0.112**
	[0.00]	[0.12]	[0.05]
gap(tttafraa)(q-1)	0.0154***	0.672***	0.547***
	[0.00]	[0.19]	[0.08]
Intervention	-0.0117	-0.417	1.587
	[0.09]	[3.91]	[1.67]
Constant	-0.00515	-0.304	-0.391
	[0.10]	[3.95]	[1.68]
Quarterly Effects	Yes	Yes	Yes
Observations		77	
AIC (model selection)		7,12	
Legend Level	0.87	0.24	0.68

Comment: see table 7.1.

Table 7.8
The VAR model; population 16 to 64 years quarterly data.

	gap(arbl)	gap(ttfafraa)	gap(tttafraa)
gap(arbl)(q-1)	0.979***	-0.190	0.465***
	[0.03]	[0.21]	[0.09]
gap(ttfafraa)(q-1)	-0.0162	0.0452	0.125**
	[0.02]	[0.12]	[0.05]
gap(tttafraa)(q-1)	-0.176***	0.720***	0.556***
	[0.03]	[0.19]	[0.08]
Intervention	.102	-0.514	1.132
	[0.60]	[3.88]	[1.70]
Constant	-0.0358	-0.325	-0.0357
	[0.60]	[3.92]	[1.72]
Quarterly Effects	Yes	Yes	Yes
Observations		77	
AIC (model selection)		10.8	
Legend Level	0.94	0.24	0.67

Comment: see table 7.1.

Figure 7.1
Impulse response model; individuals aged 16-24.

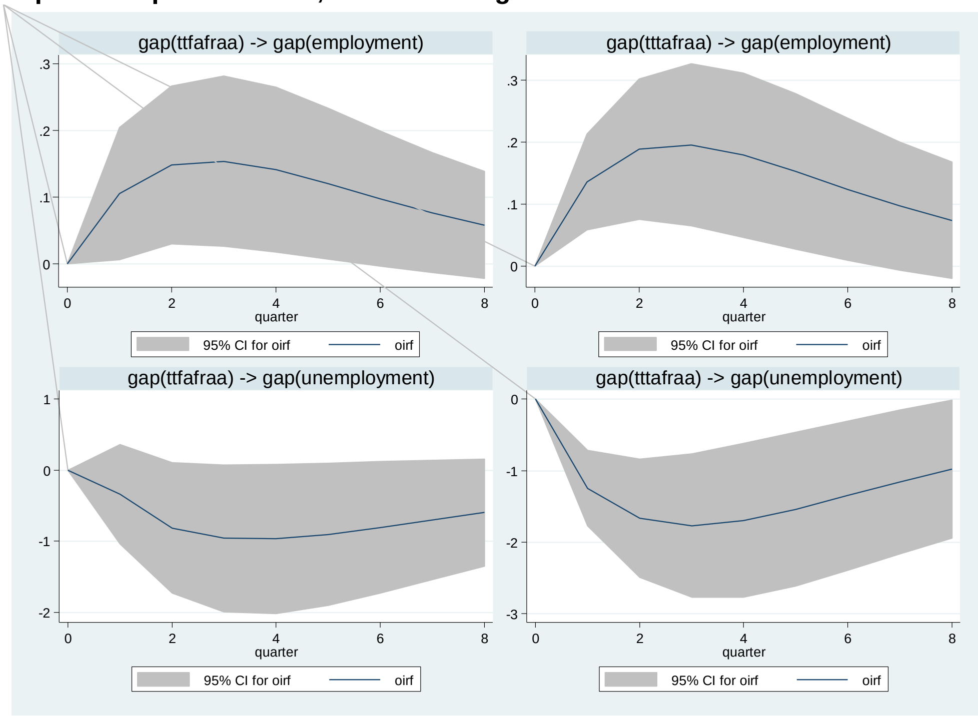
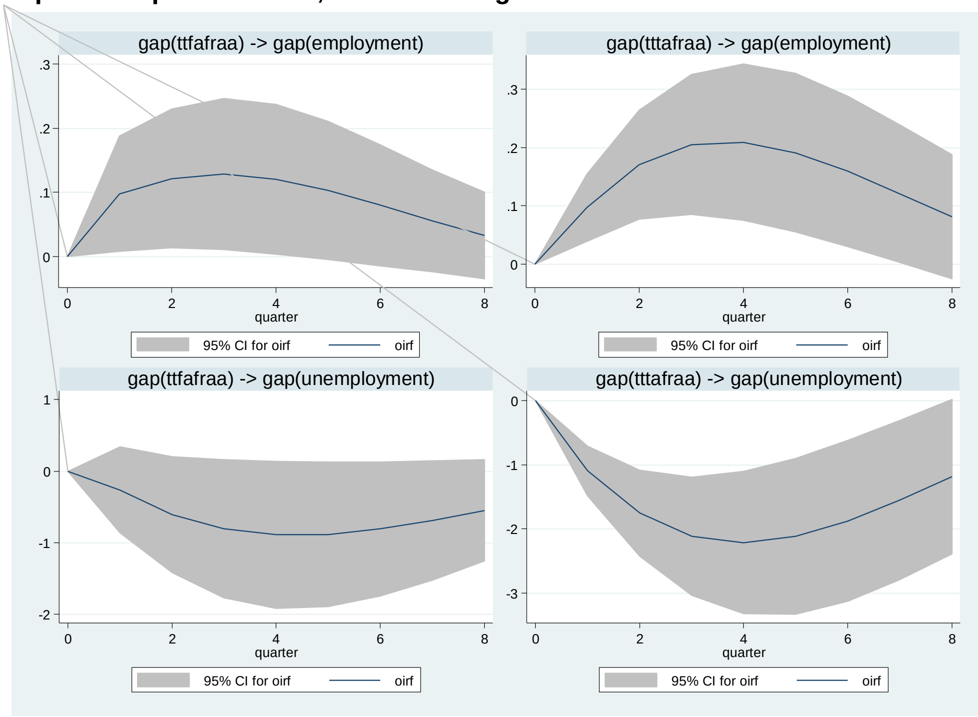


Figure 7.2
Impulse response model; individuals aged 16-64.



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