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Age-Wage Profiles for Finnish Workers

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TIIVISTELMÄ

Tässä selvityksessä pyritään mallintamaan ja ennustamaan TEL-vakuutettujen palkkojen kehitys iän mukaan. Selvityksessä sovelletaan perinteistä Box-Jenkinsin aikasarjamenetelmää, ja ennusteiden luotettavuutta on pyritty parantamaan ennusteita yhdistämällä. Aineisto käsittää suurimpien työeläkeyhtiöiden TEL-vakuutettujen palkat 18–60-vuotiaille miehille ja naisille. Aineisto kattaa vuodet 1966–2001 ja se edustaa 70–95% TEL-vakuutetusta palkasta kyseisenä aikana. Tulokset viittaavat naisten osalta selvästi siihen, että lähivuosina jatkuu 1990-luvun alun laman jälkeinen trendi. Nuoret, alle kolmekymppiset jäävät jonkin verran jälkeen yleisen ansiotasoindeksin mukaisesta kehityksestä. Muilla naisilla aina 60 ikävuoteen asti palkkakehitys näyttää ylittävän yleisen ansiokehityksen. Miesten osalta tulokset osoittavat pääosin päinvastaista kehitystä. Voidaan todeta, että valtaosa miehistä, aina 49 ikävuoteen asti, jää jonkin verran jälkeen yleisestä ansiokehityksestä. 30–39-vuotiailla ennusteet erosivat toisistaan, ja ennusteiden yhdistelynkin jälkeen kehityssuunta jäi epäselväksi. Vanhemmilla miehillä, 50 ikävuoden jälkeen, palkat näyttäisivät kasvavan yleistä ansiokehitystä nopeammin. Nämä tulokset seuraavat ansiokehityksen pitkän aikavälin trendistä. Toinen tulos, jolle saattaa olla käyttöä eläkepolitiikan suunnittelussa on se, että naiset saavuttavat hitaasti mutta varmasti miehiä palkkakehityksessä.

ABSTRACT

This study will apply the Box–Jenkins methodology model to estimate and forecast age-earnings profiles for Finnish workers. Estimation is done in a standard ARIMA framework with regressors of real economic growth and previous wages. The forecasting is based on pure time series modelling. As known, time-series models are subject to past history. However, it seems that for all ages a reasonably simple model can be found, but no one model can be applied to all ages. This is even more true when men and women are studied separately. Forecast combination provides new information for forecasting future wages. Simple combining methodology, i.e. average and median, improve in-sample forecast accuracy significantly. This is expected to give reliable forecasts for the future too.

INTRODUCTION

In modelling the economy one needs thorough knowledge of the underlying factors and their future development. This is important in generational modelling. In all economically motivated overlapping-generations models it is important to know how people's age-income profiles develop. The Finnish Centre for Pensions' long-term pension expenditure model is the prime motivating factor for this study. It is important to know and to predict the underlying wage history. What is the right retirement wage and how will it develop in the future? Knowledge of the age-income profiles is important generally as well.

It can be seen that age-income profiles have changed dramatically over the last decades in Finland (Figure 1). The change was especially clear in the 1990s. The wages of the younger generations have fallen by several per cent in real terms in reference to older generations. It is, however, presumable that it is a temporary phenomenon and that the demographic and economic forces will increase the wages of the young generations. Another interesting question is women's wages. Will women catch up with men in the wage development?

The availability of the data makes it possible to study this issue and possibly add to the number of income studies in Finland (See for example Nygård (1989), Pehkonen & Virén (1992), Asplund (1993, 1997), Hietala (1995) and Lappeteläinen (1994)). Traditionally income studies have been based on individual data. This study is based on aggregate data and time-series methods (Discussion of traditional methods in other words regression analysis is found in Freeman (1989) and Deaton (1997)).

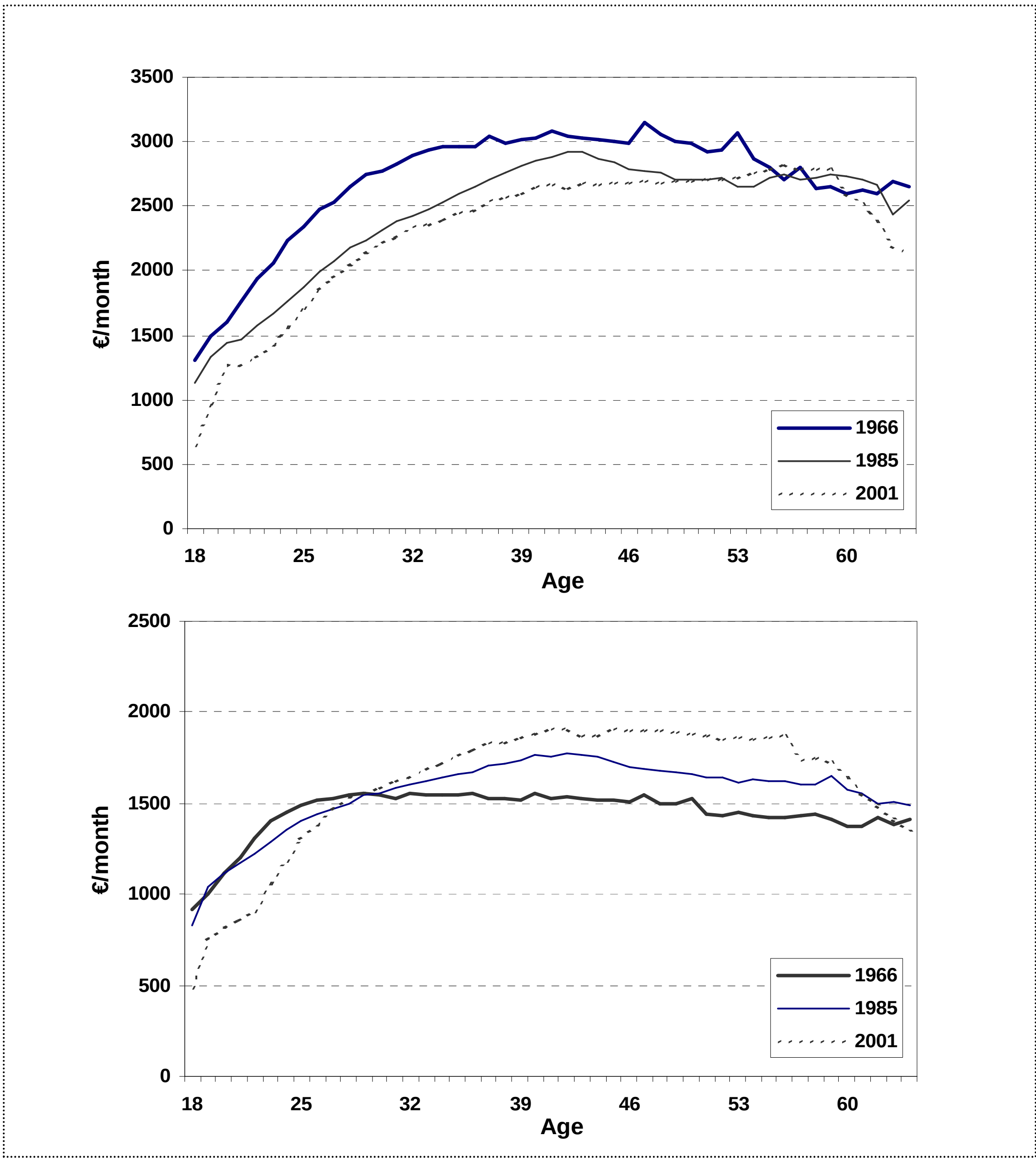

Figure 1. Cross-section wages for men (top) and women (bottom) at 2001 prices.

The structure of this paper is the following. First, we describe the data and its manipulations. Second, we build a model, which complies with time-series modelling and traditional regression modelling. The aim is to fit the best model to the data for the time period 1966 to 2001. This model also indicates the structure for the forecast model. Third, we build a forecast model, aiming to predict future wages. The best models are tested against each other and the actual data. Out-of-the-sample forecasts conclude our exercise.

DATA

The data available to us are somewhat unique. They cover the period from 1966 to 2001. They give a nice cross-section view of the last decades with fluctuations of the economy and demography. The data, kindly provided to us by the largest pension insurance companies[1], include the following information.

The wage information relates to people insured under TEL (the Employees' Pensions Act) aged 15 to 65. The wage concept is the annual wage that the employer reports to the companies. We do not have any other income information. The terms wage and income are used here in the same sense. The data show the end-of-the-year situation. Information is also available by gender. There is, on the other hand, no further information on the occupation or sector. The number of insured is available for all the age categories as well. We will not use that information in this study, however.

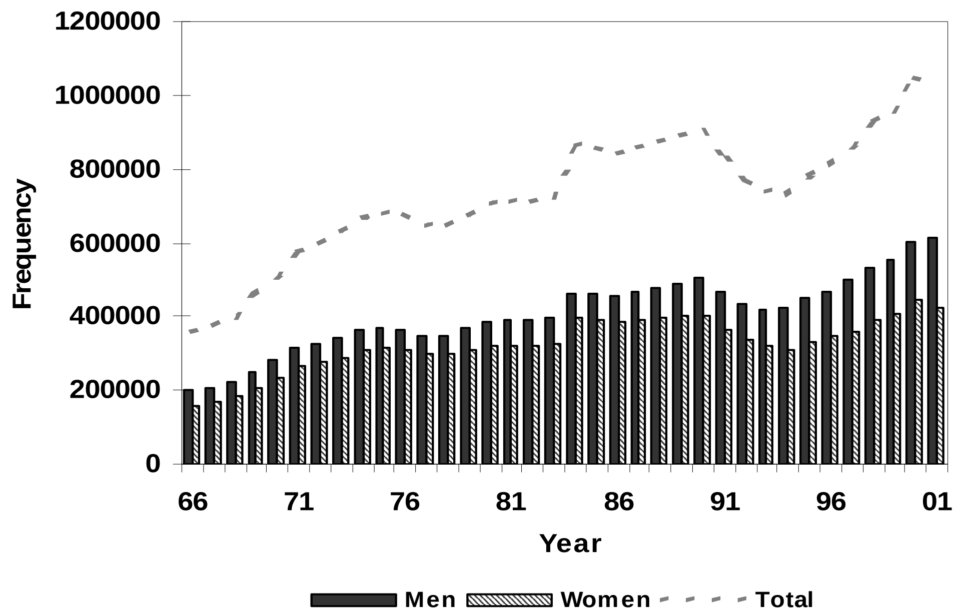

Figure 2. Total number of persons insured under TEL in the major pension insurance companies.

1 The data cover roughly 70–95% of the wages insured under TEL in the pension insurance companies.

Since the data come from administrative records, there is naturally some variation in the definition[2] of wages. For example, in the early years the employment contract limit may have excluded some young people. Still, in figure 2 it has not shown up in 1972. It can also be seen that the number of women in relation to the number of men has been very stable, as can be seen in figure 2 (appendix figure 5 shows a corresponding figure as a percentage of the population). This is even more notable since women usually work in the public sector, and public sector employers are not included in our data. However, these issues do not greatly affect the data. The statistical method is also quite insensitive for these early years.

There are some deficiencies in the data. Wages are aggregates of all age categories. There is no additional information on the underlying 'work effort' so one can not say much about the working hours.[3] Although we make notations of cohort effects, there are no individual people in the data. The data consist of 36 cross-sections added together, so one could describe it as a 'pseudo panel'.

In addition to wage information, we used a simple variable indicating overall economic performance, the yearly change in (or growth in) real GDP. Appendix figure 1 shows how this indicator has evolved throughout the years. The recession of the '90s was serious in the Finnish economy. It should be noticed that between the '60s and the '70s there were also great fluctuations in the economy. These early years were challenging in our estimations too.

An additional motivation for this real economy indicator is that it can be used when we estimate future wages.

Based on this information, we will describe and analyse age-specific wages for men and women separately. In the analysis part we will try to fit a reasonable model to the data and try to predict the future. For the analysis we will need to construct additional explanatory variables. In this kind of study there are usually variables that describe the state of the economy, unemployment, education, cohort and work experience. Some of these we can construct from the

2 The earnings limit for men as a percentage of the sample mean was roughly 20% between 1966 and 1973 (36% for women). After that it has remained at roughly 10% (15% for women). The minimum length of the employment contract was 4 months between 1 January 1965 and 1 July 1971. After that it has been 1 month. Additionally the employment contract must be valid at the end of the year to be recorded in the data.

3 In general working hours have decreased constantly during the period 1966 to 2001. As can be seen from appendix figure 2 the industrial workers' working hours have decreased by over 200 hours per year. The level of working hours is currently near the EU average.

data, but some we cannot. For predictive purposes one needs to be careful with the chosen model. A simple model is our preference. We will try this, and keeping in mind the key questions, we will be able to say something about the future.

Before we take a look at the data, we must look at some issues concerning data manipulation. We must also understand how the structure of the economy has changed over the past few decades, and how it might influence our findings.

Age groups, indexation and randomness of the data

There are several data manipulation steps before the actual analysis can begin. *First,* we check the wage series for each age from 15 to 65. We noticed that the profile changes somewhat slowly and we could base the analysis on grouped data. So there are five age groups: 20–29, 30–39, 40–49, 50–54, 55–60. Each group consists of the weighted average of the wages of the underlying ages. The weight is the proportion of the population in the data at each individual age. The age limits 20 and 60 follow from the fact that the number of employees decrease fast beyond these ages (See appendix figures 3 and 4). Accordingly it is safer to limit the analysis to the 'working age' population.

Second, there is the question of how to make our data real in values? It can be done in several ways. The first candidate is the consumer price index (CPI). In this way the wages are put in proportion to price increases. The price increase is unilateral for all employees, and in that sense it would be a good candidate. The second way is to construct an index of the data themselves, which has a merit too. The third way (which is our choice) is to make the data real in values by using an index of wage and salary earnings. With an earnings index we can see how the data develops vis-à-vis the general earnings development. The earnings and salary index also puts recent years into better perspective. (For discussion in Finnish see Kettunen (1993) and Asplund (1994)).

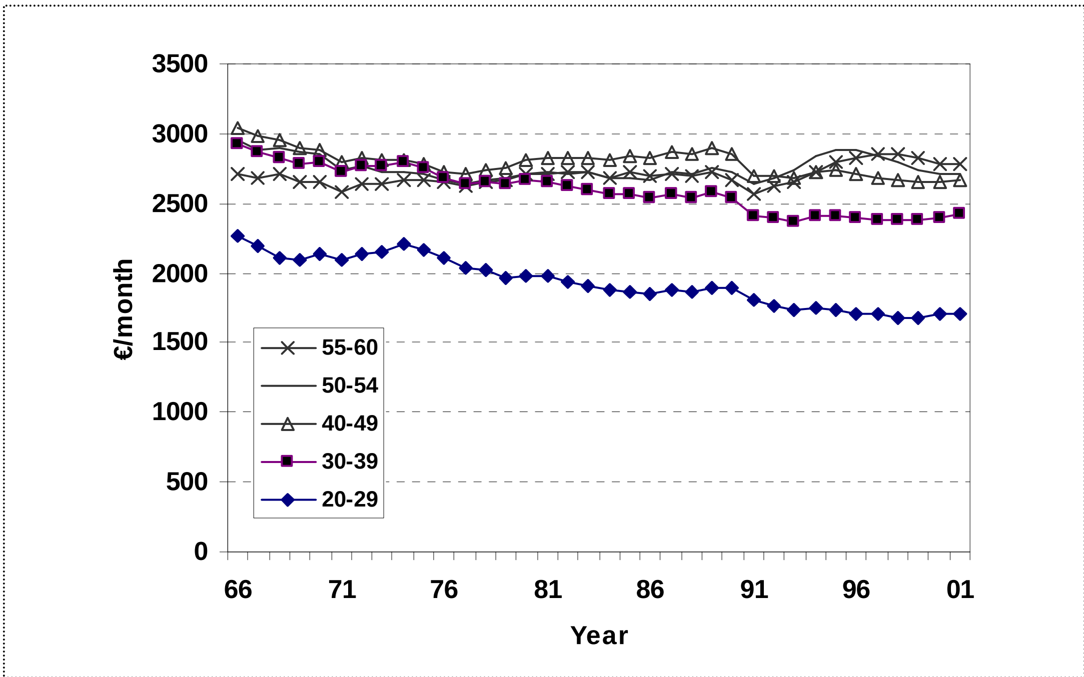

Figure 4. Average real wages for selected age groups for men. At 2001 prices.

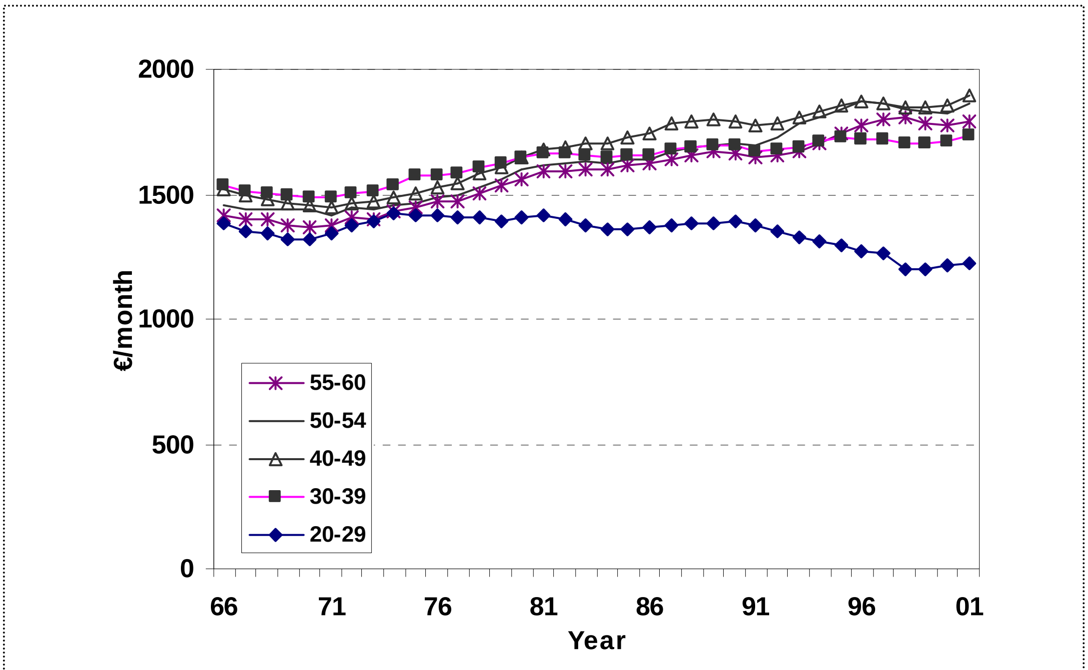

Figure 5. Average real wages for selected age groups for women. At 2001 prices.

These indexes have developed differently over the past decades. The yearly increase of the CPI from 1966 to 2001 was about 6.2 per cent on average. The earnings and salary index has increased a little faster, nearly 8.5 per cent (See appendix figure 1 for graph of yearly change of the earnings and salary index). If we construct an index of average wages of the data themselves we can see that it has followed the general earnings and salary index closely. For men it has grown 0.4 percentage points slower. For women it has grown 0.5 percentage points faster.

With different realizations we can view the wage development from various perspectives. It is plausible to think that recently, within the EMU, when prices are more stable, the earnings and salary index is a better reference point. We believe it is the right way to realize this kind of time-series data. The data appear in the level for 2001. However the estimation results are not greatly affected by realization.

Third, there is the question of the stationarity of the data. The basic requirement of time-series analysis is that it applies to data, which are an outcome of a random experiment. We tested the randomness or stationarity of our variables by the Augmented Dickey Fuller test (See e.g. Greene p. 847, 1997). The H_0 hypothesis being that the tested variable is not a random variable.

Results from tables 1 and 2 indicate that our data should be differenced once to achieve randomness. Usually indexed economic data are trend-stationary. As can be seen from tables 1 and 2, the indexation itself does not assure stationarity. Our data are difference-stationary. In the analysis we employ first and second differences. A study of autocorrelation functions also implied this manipulation.

Table 1. Results of unit-root tests, men.

Variables	Level			First difference		
	No trend	Intercept	Trend & Intercept	No trend	Intercept	Trend & Intercept
Wage2029-0 lag	-2.81***	-1.28	-2.31	-4.16***	-4.57***	-4.49***
-1 lag	-1.67*	-0.80	-3.37*	-3.65***	-4.06***	-3.97**
Wage3039-0 lag	-2.26**	-1.77	-2.62	-4.93***	-5.37***	-5.43***
-1 lag	-1.76*	-1.46	-3.01	-3.44***	-3.79***	-3.82**
Wage4049-0 lag	-1.46	-2.38	-2.44	-5.13***	-5.24***	-5.20***
-1 lag	-1.07	-2.08	-2.38	-3.17***	-3.24**	-3.22*
Wage5054-0 lag	-0.89	-2.67*	-2.49	-5.10***	-5.06***	-5.02***
-1 lag	-0.50	-2.33	-2.26	-3.07***	-3.07**	-3.10
Wage5560-0 lag	0.29	-2.67*	-2.49	-5.55***	-5.49***	-5.42***
-1 lag	0.39	-1.72	-2.54	-3.23***	-3.17**	-3.16

Table 2. Results of unit-root tests, women.

Variables	Level			First difference		
	No trend	Intercept	Trend & Intercept	No trend	Intercept	Trend & Intercept
Wage2029-0 lag	-1.46	0.21	-0.80	-3.89***	-3.89***	-4.21**
-1 lag	-0.64	-0.61	-1.79	-2.74	-2.74	-3.09
Wage3039-0 lag	2.22	-0.31	-1.70	-3.58***	-4.18***	-4.12**
-1 lag	1.97	-0.98	-2.06	-2.45	-3.09	-3.09
Wage4049-0 lag	3.35	0.30	-2.31	-2.61**	-3.64***	-3.56**
-1 lag	2.44	-0.54	-2.14	-1.51	-2.54	-2.49
Wage5054-0 lag	3.73	0.31	-2.80	-3.06***	-4.18***	-4.13**
-1 lag	2.59	-0.24	-2.95	-1.88	-2.85	-2.78
Wage5560-0 lag	3.52	0.11	-2.56	-3.11***	-4.10***	-4.01**
-1 lag	2.41	-0.57	-2.85	-2.04	-2.89	-2.81

Note for tables 1 and 2: ***, ** and * indicate significance at the 1%, 5% and 10% levels. The McKinnon critical values of ADF statistics (level) are:-2.6, -2.0 and -1.6 without trend; -3.6, -2.9 and -2.6 with intercept; -4.2, -3.5 and -3.2 with trend and intercept at the 1%, 5% and 10% levels of significance, respectively. For the first difference some of the critical values are slightly smaller.

We conclude our data manipulation by stating that the GDP change variable rejected the ADF null hypothesis at the 5% risk level.

Structural changes over recent decades

Our data cover over three decades, from the late 1960s to 2001. During this time many economic and structural changes have happened. Some of them show in the data and some should be taken into consideration when evaluating the results.

Many economic variables fluctuated strongly in the ‘70s. The nominal values of many indicators, e.g. in wages and GDP, pose a challenge when constructing variables explaining economic performance. This ‘nominal time’ can be seen for example in the sliding of wages. This occurred until recently. Many changes have affected the working hours. The latest recession made part-time jobs a more permanent phenomenon, especially for younger generations. This will show in the future in all age-income profiles. Current data cover persons insured under TEL. This group is very heterogeneous, and many changes in the industrial and agricultural structure influence the data. In part this makes it difficult to predict the future. Perhaps the best picture of the structural change in the Finnish industry can be obtained from the excellent papers by ETLA. In this study we will not be very ambitious in these matters. We feel it is sufficient to try to find a good approximation of the wage profile for the future to support our ideas. The GDP indicator is intended to catch the effect of economic growth.

Demographic developments from the early ‘40s can be seen in both sizes of cohorts and wages. The biggest cohorts in Finland were born between 1946 and 1950 (Again see appendix figures 3 and 4). In our data the wage-leader cohort (born in 1942) was born just before these so-called baby-boom generations. The wage leaders entered the workforce in the late ‘50s and obtained good wages. It is difficult to say anything concrete about the reasons for that. Apparently they were not well educated. On the other hand, we do not know the amount of their work effort. Probably they just found good positions in the labour market. In some studies it is taken as a premise that the baby-boomers suffer from relatively low wages because of their cohort size. This view is not supported by our data.

In many studies it has been shown that women of all ages receive lower wages than men (See for instance Blau & Kahn p. 92, 2000, Allén (1991)). This can be seen clearly from our data. In general women receive clearly smaller wages than men although the gender gap is not so large among young people. This is not so unusual internationally either, as can be seen from table 3. In our data the corresponding percentages are 63% (1979), 66% (1989) and

69% (1998). The change from 1979 to 1998 is then 6 percentage points. The best picture can be obtained from the following figures. The difference is clearly constant through the ages, as can be seen from figure 6.

Table 3. Female/male ratios, median weekly earnings of full-time workers.*

Country	**1979–81**	**1989–90**	**1994–98**	**Change 1979-81 to 1994–98**
Australia	0.800	0.814	0.868	0.068
Austria	0.649	0.674	0.692	0.043
Belgium	na	0.840	0.901	na
Canada	0.633	0.663	0.698	0.065
Finland	*0.734*	*0.764*	*0.799*	*0.065*
France	0.799	0.847	0.899	0.100
Germany (west)	0.717	0.737	0.755	0.038
Ireland	na	na	0.745	na
Italy	na	0.805	0.833	na
Japan	0.587	0.590	0.636	0.049
Netherlands	na	0.750	0.769	na
New Zealand	0.734	0.759	0.814	0.080
Spain	na	na	0.711	na
Sweden	0.838	0.788	0.835	na
Switzerland	na	0.736	0.752	na
United Kingdom	0.626	0.677	0.749	0.123
United States	0.625	0.706	0.763	0.138

*** Source:** Blau & Kahn (2000)

A large part of the gender gap can be explained by the fact that men and women have different occupations, and their working hours differ.

Population ageing will guarantee a strong demand for female labour. The future will show if this is truly reflected in wage development. The current situation does not prove anything of this kind. The current gender gap is affected by the fact that part-time jobs are very common for women. Another recent phenomenon is that even highly educated young women have fixed-term contracts. This will influence their life-long wage profile and they will probably never catch up with young men.

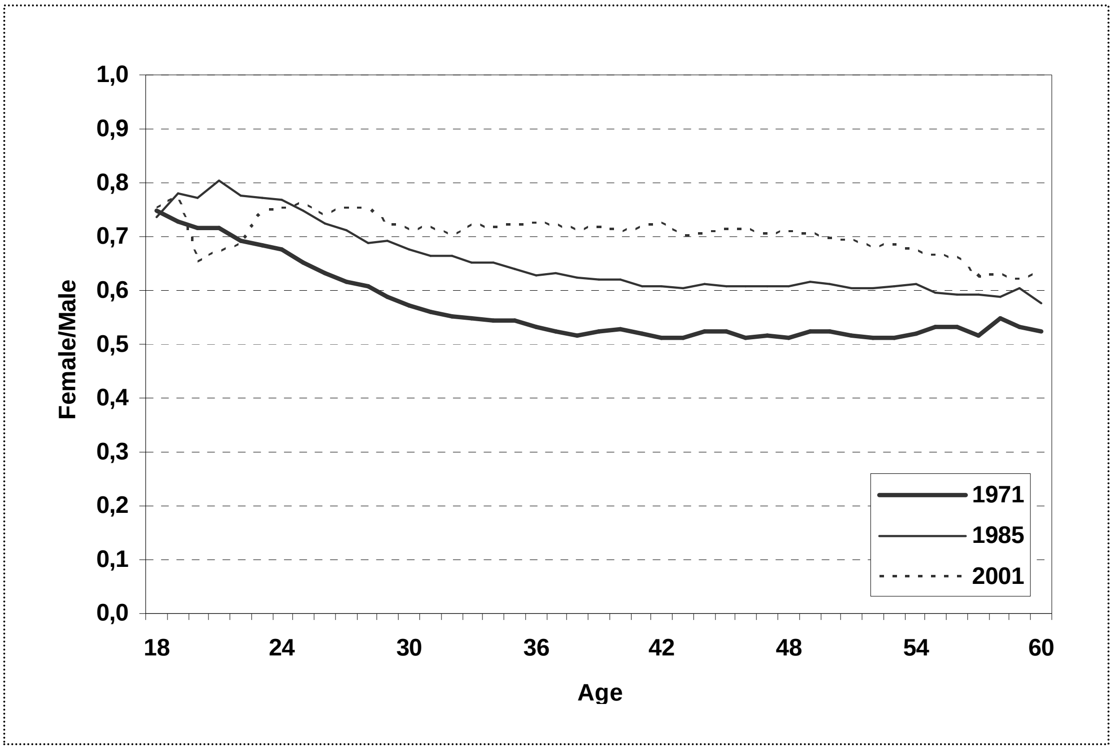

Figure 6. The gender gap in wages in 1971, 1985 and 2001.

The previous reasoning was based on the situation of supply and demand in the labour market, and the resultant wage and employment equilibrium. There is also another possible framework, which does not pose a good picture for women. Women usually work in occupations where productivity of the worker is low. This does not seem to change in the future either.

ESTIMATION

The aim of this chapter is to construct and fit a statistical model to the data. Since there is a notable difference in wages for men and for women, we begin to search for gender-specific data. We began with a wide range of models in the AR, MA and ARIMA family.

It soon became clear that high-order models were not the best choice. For example a third-order model did not converge in a satisfactory way. Second, we wanted to have the real regressors in the models. The reason for this was that the pure AR, MA or ARIMA models did not work very well on their own.

The AR, MA and ARMA models are most tractable expressed in the general form. The formulations follow Box & Jenkins (1976) and Diebold (2004). However, the notation is ours.

An autoregressive model, which essentially is a simple mathematical model in which the current value of a series (Wage, W), is linearly related to its past values plus an additive stochastic shock. Simple univariate AR(1) can be expressed as:

$$W_t = \phi_1 W_{t-1} + \varepsilon_t . \qquad (1)$$

Critical assumptions require also white noise errors, $\varepsilon_t \sim WN(0, \sigma^2)$ and $-1 < \phi_1 < 1$ for the stationary process. In lag operator form (1) can be expressed as:

$$(1 - \phi L) W_t = \varepsilon_t . \qquad (2)$$

Note that:

$$(1 - \phi L) W_t = W_t - \phi L W_t = W_t - \phi W_{t-1} . \qquad (3)$$

Thus, model (2) is equivalent to (1). In a similar fashion we can express the AR(2) model as:

$$W_t = \phi_1 W_{t-1} + \phi W_{t-2} + \varepsilon_t . \qquad (4)$$

Note that the lag operator can now be expressed as:

$$\Phi(L)W_t = (1-\phi_1 L - \phi_2 L^2)W_t = \varepsilon_t\,, \tag{5}$$

where critical assumptions require white noise errors, $\varepsilon_t \sim WN(0,\sigma^2)$ and $\phi_1 + \phi_2 < 1, \phi_2 - \phi_1 < 1$ and $-1 < \phi_2 < 1$. The AR(2) process is covariance-stationary if the inverses of all roots of the autoregressive lag-operator polynomial $\Phi(L)$ are inside the unit circle. A necessary condition for covariance-stationarity is $\Sigma_{i=1}^{p}\phi_i < 1$ (See Diebold p. 156, 2004 for discussion).

The moving average process is based on the idea that a stochastic series (like ours) can be modelled as distributed lags of current and past shocks. One property of the MA process is that low-degree models have relatively short memory regardless of parameter values.

A first-order moving average, the MA(1) process can be expressed as:

$$W_t = \varepsilon_t + \theta\varepsilon_{t-1} = (1+\theta L)\varepsilon_t\,. \tag{6}$$

Critical assumptions also require white noise errors, $\varepsilon_t \sim WN(0,\sigma^2)$. The process is covariance-stationary for any parameter values. If $|\theta| < 1$ the MA(1) process is invertible (See Diebold p. 150, 2004 for discussion). The MA(2) process is a natural generalization on the MA(1) process. Allowing more lags on the right side of the equation, the MA(2) process can capture richer dynamic patterns.

The MA(2) process can in a similar way be expressed as:

$$W_t = \varepsilon_t + \theta_1\varepsilon_{t-1} + \theta_2\varepsilon_{t-2} = \Theta(L)\varepsilon_t\,, \tag{7}$$

where critical assumptions also require white noise errors, $\varepsilon_t \sim WN(0,\sigma^2)$ .The lag operator can now be expressed as:

$$\Theta(L) = 1 + \theta_1 L + \theta_2 L^2. \tag{8}$$

The next step is to present a combination of the AR and MA components. The simplest ARMA process can be expressed as:

$$W_t = \phi W_{t-1} + \varepsilon_t + \theta\varepsilon_{t-1}\,. \tag{9}$$

Critical assumptions also require white noise errors, $\varepsilon_t \sim WN(0,\sigma^2)$. In lag operator form (9) can be expressed as:

$$(1-\phi L)W_t = (1+\theta L)\varepsilon_t . \tag{10}$$

where $|\phi| < 1$ is required for stationarity and $|\theta| < 1$ for invertibility. When these conditions are met the process can be expressed in autoregressive form as:

$$W_t = \frac{\theta(L)}{\phi(L)}\varepsilon_t . \tag{11}$$

The next step is to take the differences of the data. We use the following notation of the wage variable:

$$\begin{aligned} \Delta W_t &= W_t - W_{t-1} \\ \Delta^2 W_t &= \Delta W_t - \Delta W_{t-1} \\ \Delta^3 W_t &= \Delta W_{t-1} - \Delta W_{t-2} \end{aligned}$$

After the wage variable was made stationary by the first-order differencing, the above pure time-series models were employed. The results were not promising. The next step was to add ‘real wage’ regressors $\Delta^2 W_t$ and $\Delta^3 W_t$ to the models. A GDP regressor and a constant (*c*) were also added to the models.

Estimated model for the years 1966–2001

Using the EViews program we estimated the following time-series models with regressors. We also tried other formulations in these families. Still, the parsimony principle seemed to reduce the models to these simple variants.

First is an ARI (1,1) type model:

$$\Delta W_t = c_t + \Delta^2 W_t + \Delta^3 W_t + \Delta BKT_t + \phi \Delta W_{t-1} + \varepsilon_t . \tag{12}$$

Second is an ARI (2,1) type model:

$$\Delta W_t = c_t + \Delta^2 W_t + \Delta^3 W_t + \Delta BKT_t + \phi_1 \Delta W_{t-1} + \phi_2 \Delta W_{t-2} + \varepsilon_t . \tag{13}$$

Third is an ARIMA (1,1,1) type:

$$\Delta W_t = c_t + \Delta^2 Wt + \Delta^3 W_t + \Delta BKT_t + \phi_1 \Delta W_{t-1} + \varepsilon_t + \theta_1 \varepsilon_{t-1} . \tag{14}$$

Model Selection

The model selection was based on inspection of the residuals. The R^2 value was also indicative, though we recognize the possible problems of a R^2 measure in our data (See for example Harvey p. 120, 1993).

It was somewhat unexpected that these simple and low-degree models worked equally well for men and for women.

The Akaike Information Criterion is one way to describe the goodness of fit of time-series models (See Harvey p. 79, 1993). It is typical that this test prefers simpler models, in other words AR models in our case. Nevertheless, the difference in the test values between our models is small. So it is a matter of taste, which one to choose. We prefer simpler models.

The MAE (Mean absolute error) measure aims to quantify the level of error in our models. The definition follows:

$$MAE = \tfrac{1}{n}\sum_{i=1}^{n}\left|\varepsilon_n\right|,$$

where *n* is adjusted according to the specific model. The levels indicate that the overall error varies roughly between 0.2% and 0.5% per year for women. For men the error varies roughly from 0.3% to 0.6% per year. The recession period of the ‘90s was problematic for all models. This is no surprise, since time-series models are considered poor in estimating sudden changes in the series too. In fact, the residual evaluation also implied that the late ‘60s were problematic. As can be seen from figures 4 and 5 the class-specific series dropped suddenly in the ‘90s. This shows in the model errors. The increased error is calculated in total in our MAE measure. We wanted to evaluate model performance with the full effect of the recession.

The model residuals were plotted for all age categories and for both sexes. Examining the correlogram did not show anything distinctive. The autocorrelation functions and partial autocorrelation functions were also checked. The residual autocorrelations were tested with Ljung-Box Q-statistics, since they are probably most suitable for small samples such as ours.

Table 4. ARI(1,1) model estimates, men.

Explanatory variable	20–29	30–39	40–49	50–54	55–60
c	-0.007	-0.008***	-0.005*	-0.004	-0.002
Δ^2W	-0.912***	0.815***	0.853***	0.865***	0.897***
Δ^3W	-0.272**	-0.226**	-0.234***	-0.227**	-0.247***
ΔGDP	0.000	0.001***	0.001***	0.001**	0.001***
$ø_1$ (AR 1)	0.607***	0.425**	0.660***	0.772***	0.730***
Diagnostic statistics					
R^2	0.771	0.849	0.860	0.823	0.854
MAE	0.0063	0.0042	0.0043	0.005	0.0044
SSR	0.0019	0.00097	0.00095	0.0014	0.001
AIC	-6.578	-7.252	-7.270	-6.886	-7.180

Note: AIC is the Akaike Information Criterion. ***1%, **5% and *10%. SSR is the Sum of Squared Residuals. MAE is the mean absolute error.

Table 5. ARI(2,1) model estimates, men.

Explanatory variable	20–29	30–39	40–49	50–54	55–60
c	-0.007*	-0.005***	-0.003	-0.002	0.000
Δ^2W	1.016***	0.997***	0.983***	0.950***	0.960***
Δ^3W	-0.282***	-0.271***	-0.264***	-0.243***	-0.253***
ΔGDP	-0.000	0.000	0.000	0.000	0.000
$ø_1$ (AR 1)	1.223***	1.080***	1.200***	1.285***	1.221***
$ø_2$ (AR 2)	-0.720***	-0.768***	-0.693***	-0.740***	-0.702***
Diagnostic statistics					
R^2	0.896	0.913	0.902	0.9000	0.907
MAE	0.0042	0.0032	0.0037	0.0032	0.0033
SSR	0.0008	0.0005	0.0006	0.0007	0.0006
AIC	-7.335	-7.714	-7.525	-7.349	-7.533

Note: AIC is the Akaike Information Criterion. ***1%, **5% and *10%. SSR is the Sum of Squared Residuals. MAE is the mean absolute error.

Table 6. ARIMA(1,1,1) model estimates, men.

Explanatory variable	20–29	30–39	40–49	50–54	55–60
c	-0.004	-0.004	-0.004	-0.001	0.001
Δ^2W	0.978***	0.952***	0.943***	0.982***	0.971***
Δ^3W	-0.248***	-0.238***	-0.238***	-0.248***	-0.242***
ΔGDP	-0.000	0.000	0.000	0.000	0.000
$ø_1$ (AR 1)	0.642***	0.518**	0.563***	0.638***	0.570***
θ_1 (MA 1)	0.989***	0.944***	1.248***	0.961***	0.989***
Diagnostic statistics					
R^2	0.906	0.909	0.938	0.913	0.914
MAE	0.0035	0.0032	0.0028	0.0035	0.0031
SSR	0.0007	0.0005	0.0004	0.0006	0.0006
AIC	-7.41	-7.693	-8.030	-7.531	-7.655

Note: AIC is the Akaike Information Criterion. ***1%, **5% and *10%. SSR is the Sum of Squared Residuals. MAE is the mean absolute error.

Table 7. ARI(1,1) model estimates, women.

Explanatory variable	20–29	30–39	40–49	50–54	55–60
c	-0.000	0.004*	0.008**	0.007*	0.006*
$\Delta^2 W$	1.007***	0.998***	1.033***	1.024***	0.995***
$\Delta^3 W$	-0.307***	-0.307***	-0.287**	-0.296***	-0.289***
ΔGDP	-0.000	0.000	0.000	0.000	0.000**
$ø_1$ (AR 1)	0.793***	0.733***	0.779***	0.792***	0.742***
Diagnostic statistics					
R^2	0.798	0.817	0.842	0.828	0.812
MAE	0.0051	0.0028	0.003	0.0035	0.0034
SSR	0.0013	0.0004	0.0004	0.0006	0.0006
AIC	-6.933	-8.129	-8.036	-7.661	-7.711

Note: AIC is the Akaike Information Criterion. ***1%, **5% and *10%. SSR is the Sum of Squared Residuals. MAE is the mean absolute error.

Table 8. ARI(2,1) model estimates, women.

Explanatory variable	20–29	30–39	40–49	50–54	55–60
c	-0.002	0.004***	0.007***	0.007***	0.007***
$\Delta^2 W$	1.030***	0.987***	0.979***	0.989***	0.980***
$\Delta^3 W$	-0.295***	-0.285***	-0.251***	-0.266***	-0.257***
ΔGDP	-0.000	0.000	0.000	0.000	0.000
$ø_1$ (AR 1)	1.537***	1.376***	1.473***	1.415***	1.310***
$ø_2$ (AR 2)	-0.868***	-0.733***	-0.725***	-0.762***	-0.728***
Diagnostic statistics					
R^2	0.917	0.913	0.920	0.911	0.908
MAE	0.0034	0.002	0.002	0.0023	0.0025
SSR	0.0005	0.0001	0.0002	0.0003	0.0002
AIC	-7.726	-8.80	-0.725	-8.241	-8.386

Note: AIC is the Akaike Information Criterion. ***1%, **5% and *10%. SSR is the Sum of Squared Residuals. MAE is the mean absolute error.

Table 9. ARIMA(1,1,1) model estimates, women.

Explanatory variable	20–29	30–39	40–49	50–54	55–60
c	-0.000	0.005*	0.009**	0.008**	0.008**
$\Delta^2 W$	0.998***	1.008***	1.016***	1.009***	-0.968***
$\Delta^3 W$	-0.258***	-0.278***	-0.261***	-0.260***	-0.239***
ΔGDP	-0.000	-0.000	-0.000	-0.000	0.000
$ø_1$ (AR 1)	0.738***	0.670***	0.750***	0.708***	0.645***
θ_1 (MA 1)	0.945***	0.935***	0.939***	0.942***	0.949***
Diagnostic statistics					
R^2	0.913	0.916	0.932	0.921	0.912
MAE	0.0033	0.0019	0.0019	0.0025	0.0024
SSR	0.0005	0.0001	0.0001	0.0002	0.0002
AIC	-7.719	-8.843	-8.819	-8.377	-8.410

Note: AIC is the Akaike Information Criterion. ***1%. **5% and *10%. SSR is the Sum of Squared Residuals. MAE is the mean absolute error.

With lag sizes 5 the models mostly passed the test at the 5% risk level[4]. The correlations behaved best in the ARIMA model. There were some cases where the value of autocorrelation was near the critical value (0.254=$\pm\sqrt{\frac{2}{31}}$). However, we concluded that there is no need to change models. These simple models describe a variety of wages well, which was somewhat surprising.

Some idea of how the models generally behaved can bee seen in appendix figure 6.

Results

As can be seen in the ARIMA model, men aged 40–49 have a high MA coefficient (1.248). This has no practical meaning at this point. It only means that the model could not be used in forecasting anyway (See for instance Greene p. 829, 1998). Overall the model is stationary and the results are valid.

For ARIMA models one can also see that the AR and MA coefficients differ in a satisfactory way, in other words overparametrization is not a problem here.

The constant (*c*) has some role in these models. For men the effects are mixed in these models. It seems to have some statistical role in the ARI(1,1) model for the age groups 30–39 and 40–49. There is no statistically significant effect in the ARIMA model. For women there is certainly some role for the constant, especially in the AR(2,1) model. The constant has a distinctive role in forecasting, yet we wanted to test it in estimation as well.[5]

Let us finally take a critical view at the effects of GDP. For men the effect is clear only in the ARI(1,1) model. The positive coefficients indicate that wages are positively related to overall economic growth. For women this is not so obvious. This is a little surprising, since the original data indicate positive growth. We did some experiments with data divided into small and major employers[6]. For major employers the positive relation was clear both for men and for women.

4 Diebold (p. 139, 2004) argues that lag size should be near $\sqrt{T}$.

5 Box & Jenkins (p. 92–93, 1976) warn about adding a constant term since it proposes a deterministic trend in the model.

6 The major employer has more than 49 employees.

FORECASTING

In practice predictions are almost invariably made with estimated parameters only. However, in the last chapter the estimation was based on a time-series model with regressors, i.e. previous yearly changes of wages and GDP. That model can only be applied to estimation. The aim was to build a model using all possible wage information. Another aim was to test the importance of the GDP variable.

Forecasting is not possible in this framework. It would require forecasts of the *future* yearly changes in wages. We do not explore that here, but we turn our attention and analysis to pure time-series modelling. This means that we drop the real component out and start elaborating on pure time-series models such as presented in equations 1,4,6,7 and 9. Of course we tried numerous variants in the AR, MA and ARIMA families.

First we will study in-sample forecasts and their performance against observed data. The second stage is to predict the future.

As an example of AR forecasting[7] let us look at how a so-called chain rule would work in an AR(2) model. Following equation (4) it can be shown that the first period forecast is:

$$\widehat{W}_{t+1} = c + \phi_1 W_t + \phi_2 W_{t-1}. \qquad (15)$$

The second period forecast is:

$$\widehat{W}_{t+2} = c + \phi_1 \widehat{W}_{t+1} + \phi_2 W_t. \qquad (16)$$

The third period forecast is:

$$\widehat{W}_{t+3} = c + \phi_1 \widehat{W}_{t+2} + \phi_2 \widehat{W}_{t+1}. \qquad (17)$$

This can be continued until the end of the forecast period.

7 Forecasts are naturally made on differenced data, but here we use a simpler notation.

The moving average process is a little different and in our case it depends heavily on the constant term. For example a MA(2) process as in equation (7) can be used in forecasting. A first period forecast is:

$$\widehat{W}_{t+1} = c + \theta_1 \varepsilon_t + \theta_2 \varepsilon_{t-1} . \qquad (18)$$

The second period forecast is:

$$\widehat{W}_{t+2} = c + \theta_2 \varepsilon_t . \qquad (19)$$

The third period forecast is:

$$\widehat{W}_{t+3} = c . \qquad (20)$$

The constant *c* would be the forecast until the end of the prediction period.

Following equation (9) we can make forecasts in the ARMA family as well. For example an ARMA(1,1) process as in equation (7) can be used in forecasting. A first period forecast is:

$$\widehat{W}_{t+1} = c + \phi W_t + \theta \varepsilon_t \qquad (21)$$

The second period forecast is:

$$\widehat{W}_{t+2} = c + \phi \widehat{W}_{t+1} \qquad (22)$$

This can be continued until the end of the forecast period as in the AR case.

After some work with the data it became clear that a forecast based on one model would be problematic. Combining forecasts could be in order. The idea came from excellent writings of Clemen (1989) and Makridakis et al. (ch. 11, 1998). We follow here simple methods as suggested for instance by Armstrong (1989) and Chatfield (p.103, 2000).

The main idea is to forecast the future, which in our case means beyond the year 2001. The preliminary work is done via in-sample forecasting.

In addition to time-series forecasting we wanted to experiment with some more simple methods. Since smoothing methods are relatively simple and appealing, we employed Holt's method. The method is discussed in more detail in Pindyck & Rubinfeld (p. 480, 1998) and Makridakis et al. (ch. 4, 1998).

The basic idea of exponential smoothing methods is that it employs an exponentially weighted moving average model for smoothing. In our application this method assigns heavier weights to recent values of the wage.

In our experiment the smoothed wage series ($\widehat{W}$) is found from two recursive equations (23 and 24) and depends on two smoothing parameters α and γ, both of which must lie between 0 and 1.

$$\widehat{W}_t = \alpha \widehat{W}_t + (1-\alpha)(\widehat{W}_{t-1} + T_{t-1}) \tag{23}$$

$$T_t = \gamma(\widehat{W}_t + \widehat{W}_{t-1}) + (1-\gamma)T_{t-1} \tag{24}$$

Here T_t is a smoothed series representing the average rate of increase in the smoothed wage series ($\widehat{W}_t$). The trend is added when the smoothed wage series is calculated. This prevents the forecasted wage series from deviating too far from recent values of the original wage series. An *l* period (in our in-sample exercise eight period) forecast can be generated from equations (23) and (24) using

$$\widehat{W}_{T+l} = \widehat{W}_T + lT_T \; . \tag{25}$$

Thus the *l* period forecast takes the most recent smoothed value $\widehat{W}_T$ and adds an expected increase lT_T to the long-term trend.

In our case we naturally use the original wage series (as seen in figures 1 and 2), since the exponential smoothing method requires no differencing.

In-sample forecast - 1994 – 2001

A positive feature of in-sample forecasting is that we can compare the models against true values. Reader should notice that in-sample forecasts are genuine forecasts, as the parameters are based on the sample period 1966–1993.

We begin with a wide range of models. The prediction accuracy in the end determines which models will be accepted for out-of-sample forecasting. From table 10 column 1 one can see our variants.

Our basic objective is to see how closely the forecasted model tracks its corresponding data series. There are several possible measures to choose. We choose one common measure; root-mean-square percentage forecast error. The RMPSE for our wage variable W_t is defined as

$$RMSP\ error = \sqrt{\frac{1}{T}\sum_{t=1}^{T}\left(\frac{\widehat{W}_t^{s} - W_t^{a}}{W_t^{a}}\right)^2}$$

where $\widehat{W}_t^{s}$ is the forecasted value of W_t . The actual value is W_t^{a} and T is the number of periods, i.e. the forecasting years 1994 to 2001.

Of course such a wide range of models vary in performance. There are many reasons for that. But, we limited the models with the following criteria:

- Models with problems in parameter estimation were excluded
- Models with over 5% RMSP error measure were excluded

We try to keep all possible models in our analysis. This means that we do not prefer any model for itself. A low R^2 value does not mean that the model is bad for forecasting. The information criterions do not help much in our case since the AIC values are so close to each other that no evaluation can be based on them (See appendix tables 1 and 2). As a sidetrack it can be noticed that the Holt & Winters method works well against time series models especially for women.

In empirical studies it has been shown that the simple average performs well against so-called optimal models. Optimal can also mean some optimal combination of models, where the weighting is based on error measures (See recent paper by Zou and Yang (2004)). In our case the weighting is based on a RMSPE measure. Here we study the following combination alternatives:

- Weighted (by RMSPE)
- Median
- Mean

The median seems a good candidate too, since it might offer additional benefits in forecast accuracy. In any case, the median is more insensitive to extreme values, as we will see.

Table 10. Root-mean-square percentage error measures for the models.*

Model	Men				
	20-29	30-39	40-49	50-54	55-60
ARI(1,1,0)	**0.014**	**0.027**	**0.012**	**0.033**	*0.052*
ARI(2,1,0)	**0.021**	**0.022**	**0.033**	*0.224*	*0.056*
ARI(1,2,0)	**0.021**	**0.019**	**0.015**	*0.129*	**0.048**
ARI(2,2,0)	**0.038**	*0.063*	**0.037**	*0.092*	**0.036**
ARIMA(1,1,1)	**0.022**	**0.020**	*0.054*	**0.030**	**0.047**
ARIMA(2,1,1)	**0.023**	**0.024**	*0.058*	*0.171*	*0.050*
ARIMA(1,1,2)	**0.03**	**0.024**	*0.063*	**0.027**	~~0.048~~
ARIMA(2,1,2)	~~0.012~~	**0.025**	*0.053*	*0.063*	**0.045**
ARIMA(1,2,1)	*0.105*	~~0.108~~	**0.018**	*0.056*	*0.051*
ARIMA(2,2,1)	*0.104*	**0.023**	**0.032**	*0.050*	*0.061*
ARIMA(1,2,2)	*0.103*	~~0.094~~	~~0.083~~	~~0.054~~	~~0.088~~
ARIMA(2,2,2)	*0.089*	*0.085*	~~0.078~~	*0.068*	~~0.074~~
IMA(0,1,1)	**0.012**	**0.029**	**0.012**	**0.035**	*0.058*
IMA(0,1,2)	**0.013**	**0.018**	**0.038**	*0.066*	*0.061*
IMA(0,2,1)	*0.110*	~~0.087~~	**0.020**	*0.063*	**0.041**
IMA(0,2,2)	*0.104*	*0.099*	**0.027**	~~0.113~~	~~0.042~~
Holt & Winters	**0.042**	*0.050*	**0.031**	**0.033**	*0.059*

Model	Women				
	20-29	30-39	40-49	50-54	55-60
ARI(1,1,0)	*0.063*	**0.018**	**0.034**	**0.028**	**0.030**
ARI(2,1,0)	*0.059*	**0.021**	*0.051*	*0.109*	**0.026**
ARI(1,2,0)	**0.019**	**0.034**	**0.050**	*0.125*	**0.027**
ARI(2,2,0)	**0.026**	**0.015**	*0.072*	*0.111*	**0.027**
ARIMA(1,1,1)	*0.063*	**0.025**	**0.042**	**0.027**	**0.022**
ARIMA(2,1,1)	*0.061*	**0.029**	*0.054*	*0.116*	**0.027**
ARIMA(1,1,2)	~~0.056~~	**0.026**	*0.072*	*0.123*	**0.023**
ARIMA(2,1,2)	*0.064*	**0.015**	*0.069*	~~0.025~~	**0.023**
ARIMA(1,2,1)	**0.023**	**0.016**	*0.065*	*0.072*	**0.025**
ARIMA(2,2,1)	**0.026**	~~0.026~~	*0.072*	*0.072*	**0.039**
ARIMA(1,2,2)	~~0.021~~	~~0.022~~	*0.197*	*0.076*	**0.041**
ARIMA(2,2,2)	**0.031**	~~0.015~~	*0.168*	*0.203*	**0.043**
IMA(0,1,1)	*0.067*	**0.013**	**0.016**	**0.019**	**0.033**
IMA(0,1,2)	*0.054*	**0.022**	**0.041**	*0.054*	**0.031**
IMA(0,2,1)	**0.027**	**0.021**	**0.034**	*0.065*	**0.043**
IMA(0,2,2)	**0.033**	**0.021**	**0.227**	*0.074*	**0.047**
Holt & Winters	**0.027**	**0.010**	**0.024**	**0.027**	**0.045**

* Cross out indicates that the model has been dropped because of lack of significance or other problems. Italics indicate that the model has been dropped because of over 5% error. Bold indicates that the model has been accepted for further analysis.

Out-of-sample forecast - 2002 – 2010

Forecasting performance for the period 1994 to 2001 was the basis for the model selection criterion for forecasting future wages. Parameters are now re-estimated for the sample 1966–2001.

One should keep in mind that differencing a series can have a large effect on the forecast (See Makridakis et al. p. 371, 1998 and Harvey p. 115, 1993). In our case the data were differenced once, and including a constant term will lead to a linear trend forecast in the long term. This means that the forecast will follow a linear trend where the slope of the trend is equal to the fitted constant. In some cases our data are differenced twice and a constant term is included. This means that the forecast will in the long term follow a quadratic trend based on the trend at the end of the data series. This is reflected in the prediction intervals too. Since our approach is based on combining forecasts, we do not show the forecast variance here.[8]

The Holt & Winters method for real GDP growth indicates a slight growth from 1% per year in 2002 to 1.3% per year in 2010.

For men the results are partly expected and partly new. The downward slope for the age group 20–29 is something that one could expect from figure 4. The slight upward trend for the age groups 40–49, 50–54 and 55–60 is also expected. On the other hand, the rate of growth for the age group 55–60 is surprising.

The three forecast-combining methods provide very uniform forecasts for the age groups 50–54 and 55–60. Our measures differ substantially for the age group 30–39. The median forecast differs from the weighted average in 2010 by roughly 7 per cent. As the weighted average predicts basically no growth between 2001 and 2010, the median forecasts a 7.2 per cent drop in wages. It seems that some models (which worked fine in the in-sample test) predict very high growth. Also, this will bend the average and weighted average upwards. The same happens in the age group 40–49. We think this is just one example why combining forecasts is necessary.

8 Chatfield (p.103, 2000) argues that there is no theoretically obvious way to compute prediction intervals.

For women the methods differ only slightly. The overall data for women are totally different from those for men, as can be seen from figures 4 and 5. Apart from the age group 20–29 there is visible growth for all age groups over the whole period. For the youngest age group there seems to be only a slight drop in relation to the wages and salary index. Our models seem to work well with women's data. Also, the downward-sloping age group 20–29 does not differ so much.

Overall the wage level for women has been lower. Still, for some time women have been converging towards men. This seems to continue in the near future. Figures 9 and 10 also show that the recession period was not so marked in this data.

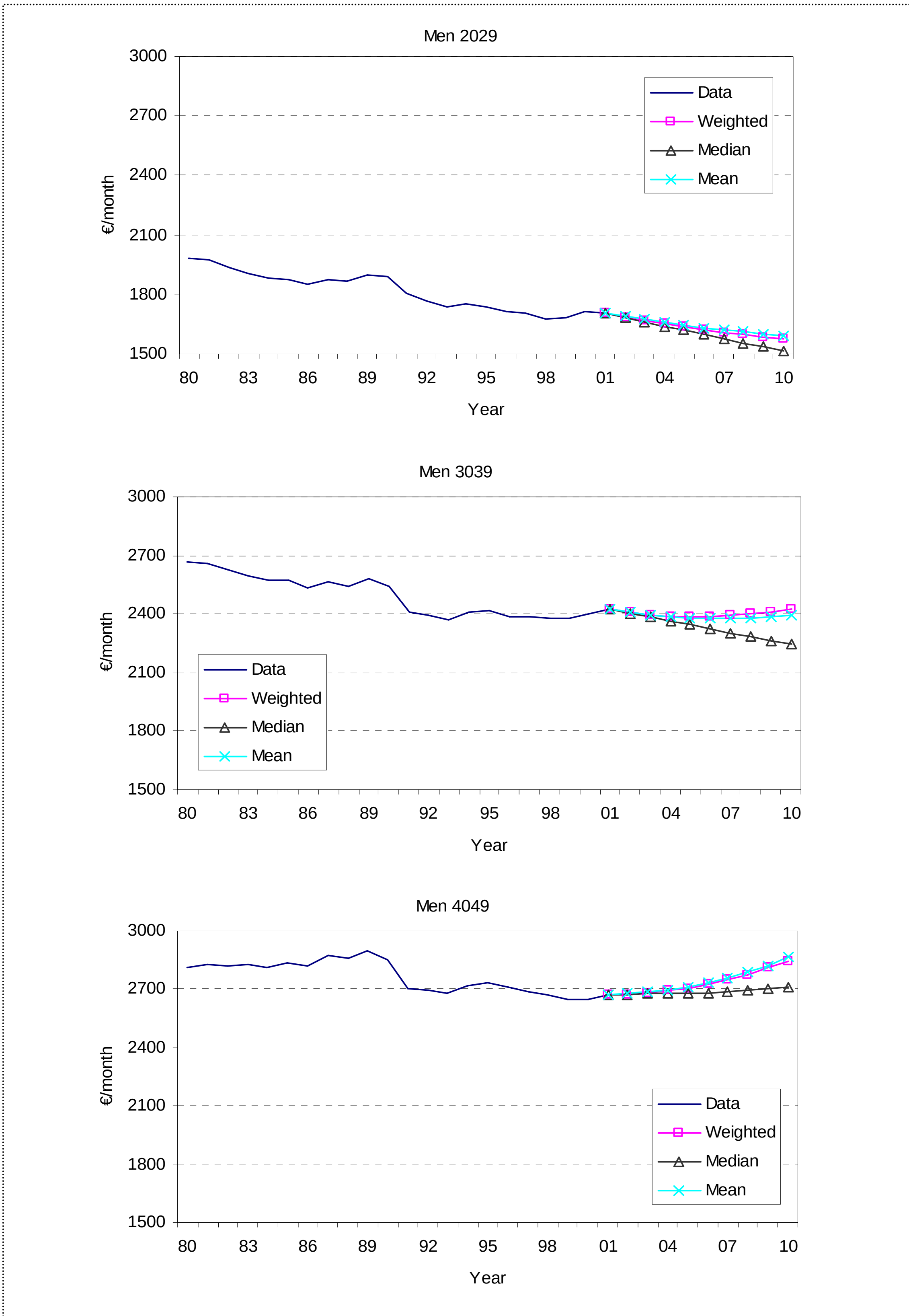

Figure 7. Forecasts for age groups, men.

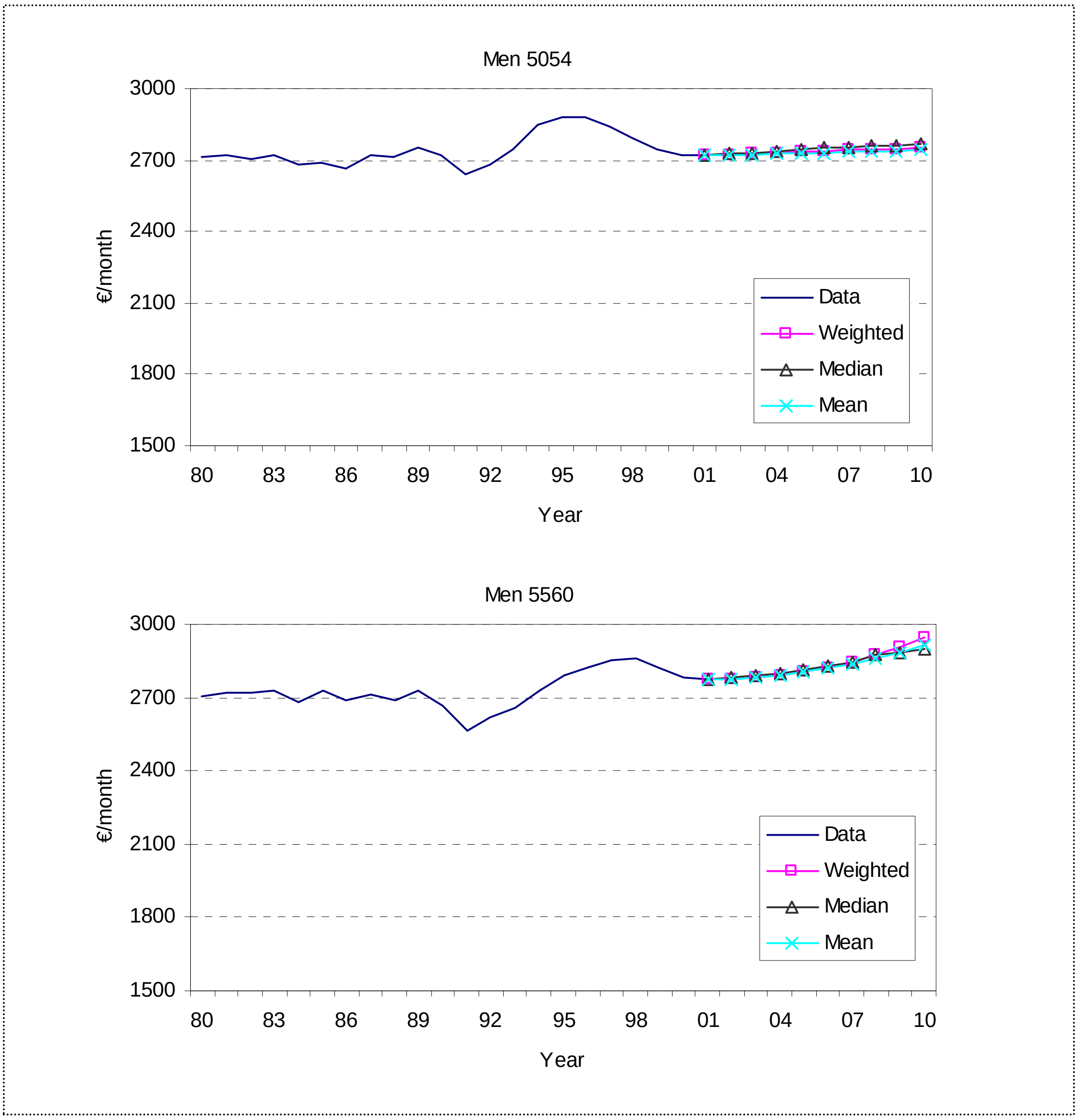

Figure 8. Forecasts for age groups, men.

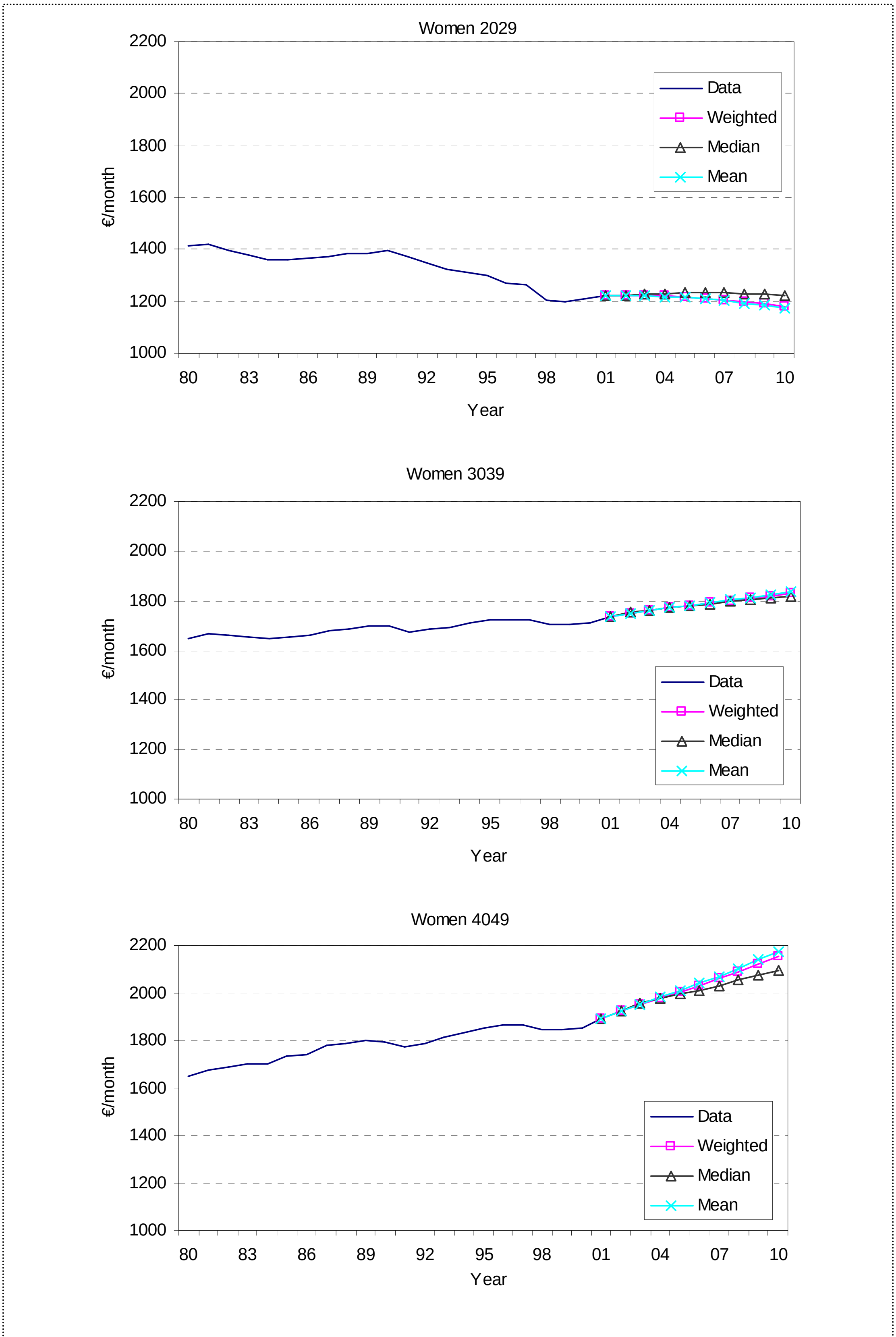

Figure 9. Forecasts for age groups, women.

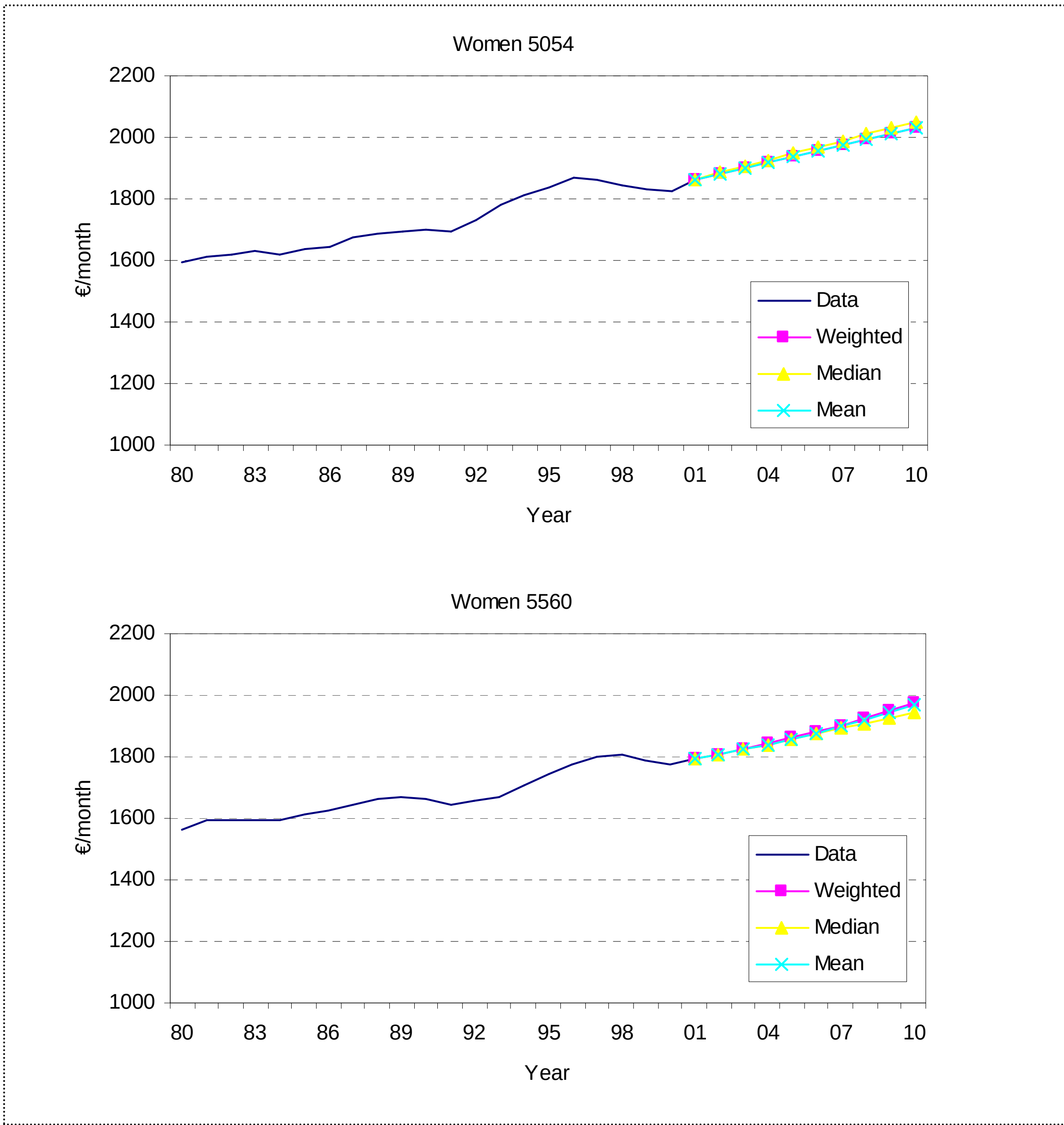

Figure 10. Forecasts for age groups, women.

An application to cross-section forecasting

The previous models can be used to calculate age-specific forecasts. In the following we provide a median of underlying forecasts for the ages 18 to 60. As could be seen from figure 1 the cross-section profile has changed over the years. Figures 11 and 12 show how this development would continue in light of the median forecast.[9] The dotted line shows the most recent data point in our analysis. The even lines show the situation some years ahead. There are several issues involved.

The first thing to notice are the ages of a drop in wages and the ages of growth in wages. There is a noticeable difference between men and women. For men the ages for which a drop will continue range from 18 to 50. Older men will gain in wages. For women this story is different. We expect some growth for women older than 30 years old.[10]

Second, one should notice that our yardstick is the general earnings development, which means that the growth must be above the earnings and salary index in order to show positive results here. The story would be somewhat different with consumer price indexation. For the cohort level the story is also different. The cohorts naturally move along these profiles and eventually they will gain even in this sort of aggregate data. The issue of cohort wages and cross-section wages is treated for example in Creedy (1985). We do not elaborate on it here.

Third, the inspection of individual model estimates revealed that some models are highly sensitive to the initial values of 2000 and 2001. Also, as the forecast period increases the forecasts explode to unlikely values. This is yet another reason to combine forecasts.

Fourth, it must be kept in mind that these phenomena are subject to structural issues in the labour market. It would be a mistake to continue these forecasts for decades. We think that some changes especially in the young age groups are about to happen eventually. This would change these profiles notably.

9 We don't pre-select models here. The median is calculated over all the models presented in table 10.

10 As a reference the average would predict slightly higher wages for men. For 2006 the average would be 0.5% higher and for 2010 about 2.5% higher. For women the median is slightly over in the beginning (0.2% for 2006) and then the average gets higher (0.1% for 2010).

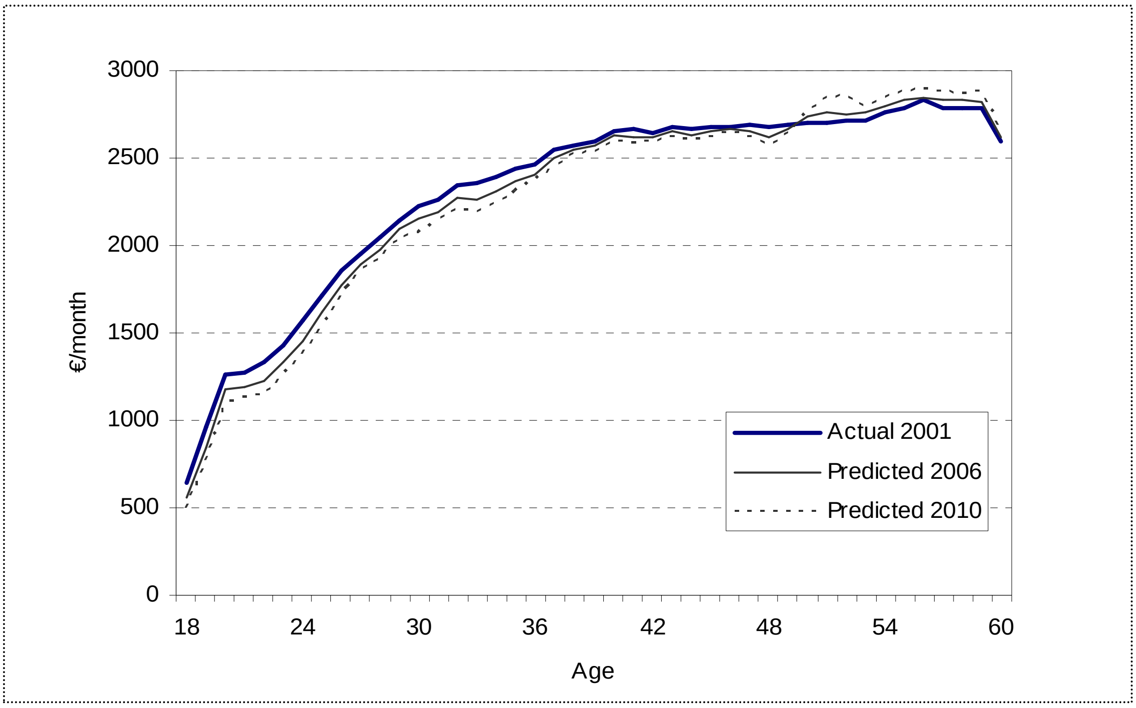

Figure 11. Median wages in selected years, men.

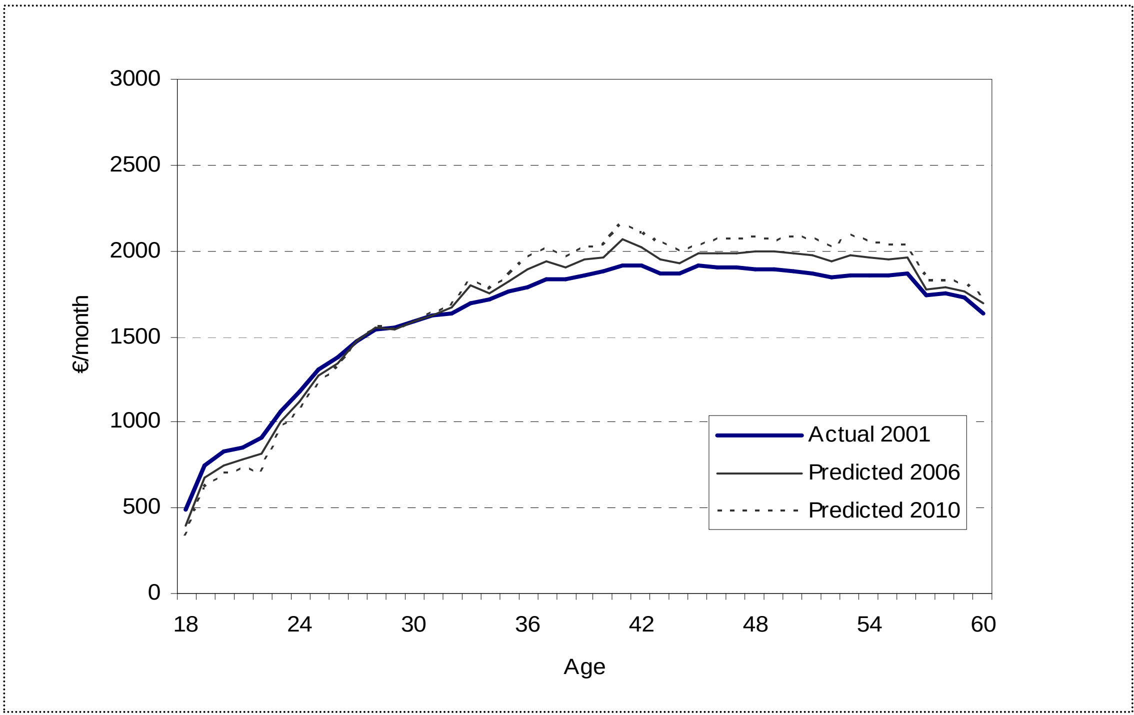

Figure 12. Median wages in selected years, women.

A preliminary test

The data are updated every fall. During this study the data were updated to 2002. We did not use the data in our analysis, but we used them as a reference point. The year 2002 is our first out-of-sample forecast year, so it is now interesting to compare our median forecast for that year to the actual data.

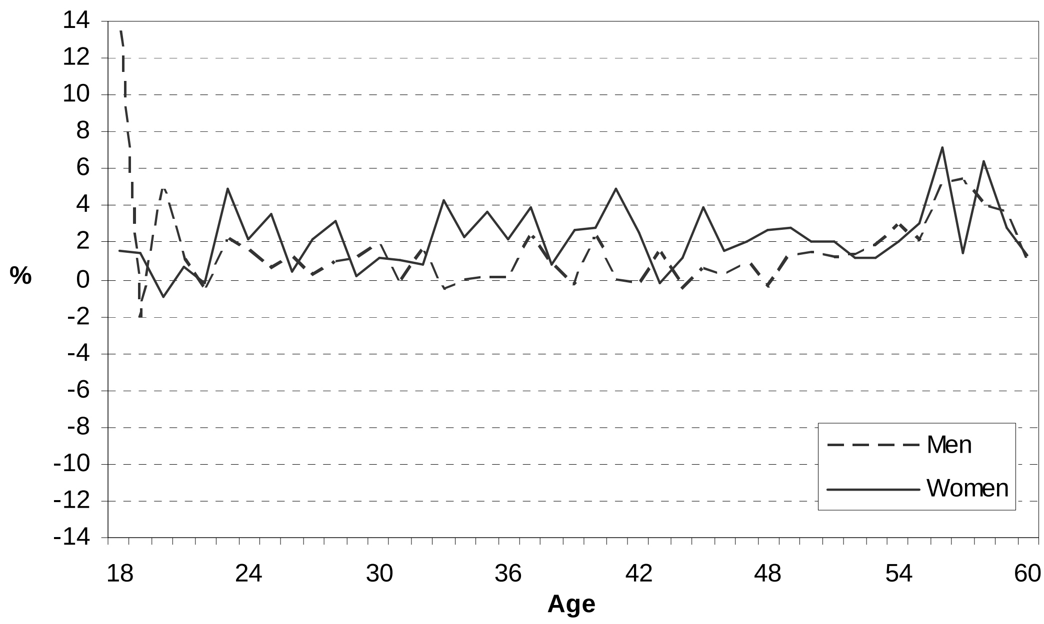

Figure 13. Forecast vs. actual in 2002.

There is one critical issue here. Namely, since we are forecasting real values (2001 level) it is necessary to adjust market-level wages of 2002 to the level of 2001 (this could be done in several ways). It is here done with the 3.5% earnings growth[11]. The most recent data are multiplied by .965 to get comparable results.

Zero is the reference level for a perfect forecast. As can be seen from figure 13 there is typically some over-estimation in some ages. This seems to be true especially for women. Table 11 shows the levels of some statistical measures. These numbers are calculated over the ages 18 to 60. It also seems that our

11 The earnings and salary index indicates 3.5% earnings growth between 2001 and 2002.

median forecast is too optimistic, compared to the adjusted market-level wages of 2002. Depending on the measure our median predicts roughly one per cent higher monthly wages for men, and correspondingly two per cent higher wages for women.

Table 11. Some statistics of short-term prediction performance.

	Men	Women
Median	1.06	2.09
Mean	1.51	2.25

Male-female wage difference in the future

One motivation for this study was to study how the wage difference between men and women develops. Will women catch up with men in wages in light of these calculations?

Again these results are based on our median forecasts. In this we simply divide women's wages by men's wages. It seems that in all age groups the development we have seen in past decades will continue in the near future (See dotted line in figure 14). There are some issues that should be kept in mind here.

First, these figures are for persons insured under TEL. It is known that women represent a high proportion in the public sector, and the wage difference is a little smaller there. So in the overall workforce women are on a higher level. This could be seen in table 3, where the difference has varied between 75% and 80%. Yet, the trend in official statistics and our data indicate a very similar trend from the '70s through the '90s.

Second, the labour supply is not controlled in this study. It is known that women work less overtime. This probably shows in our data, especially in the level comparisons.

Third, one should not confuse cohort effects here. Younger cohorts are more educated, especially women. Probably cohort studies would indicate a much faster narrowing wage gap. In time this will show in our cross-section data too.

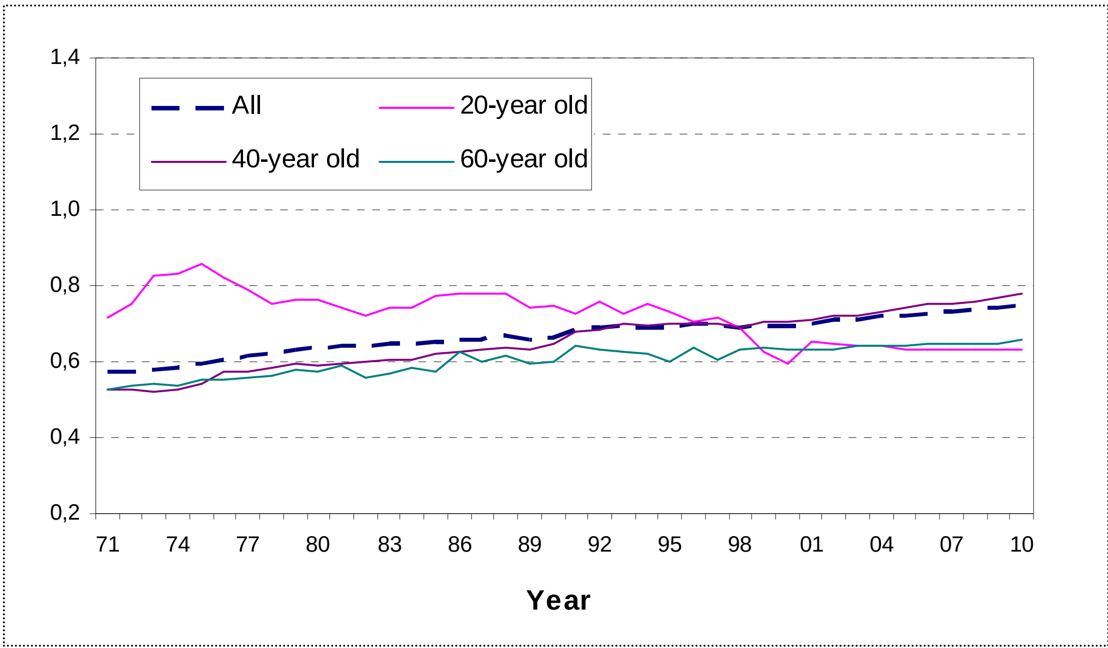

Figure 14. Women's wages in relation to men's wages in 1971–2010.

CONCLUSION

Our study is a new way to study wage profiles in aggregate data. Time-series modelling has rarely been applied to study and forecast age-specific wages. Results indicate that this can be done succesfully, and reasonably simple models can be applied to all ages both for men and for women. Typically time-series modelling follows conventional rules, and with careful work this can be successful. Yet, there are some inherent problems in this approach. In this study the approach has been different. In fact we propose combining forecasts to improve accuracy.

Using several models of the AR, MA and ARIMA family we did in-sample forecasts for the period 1994 to 2001, aiming to find reasonable models for out-of-sample forecasting of workers aged between 20 to 60 years. Three simple methods (i.e. median, average and weighted average) are presented as our out-of-sample forecasts for the years 2002 to 2010.

For women the results are uniform, the long-term trend seems to continue. A vast majority of working-age women gain in earnings growth. Results are the same regardless of the measure. For men the results are different since a majority of young to middle-aged men will phase down in the wage development. The over 50 year olds are gainers in this study. The individual forecasts are however mixed for those aged between 30 and 39 years, which is the key age for earnings development, where individual models give a wide variety of forecasts. This is why forecast combination is necessary in out-of-sample calculations.

As a by-product of these forecasts we plotted the male-female wage difference as well. It seems that the gap will continue narrowing. This is probably useful information for the pension insurance industry.

Still, the question remains: Could the wage trends really continue along these lines? The statistical answer here is based on over 35 years of data. So one can only speculate on structural issues and their effects.

This study has applied a time-series approach to age-specific data. The next natural step would be to study cohort wages. Another step is to study whether cohort sizes have some effect on wages, and whether forecasts could be improved.

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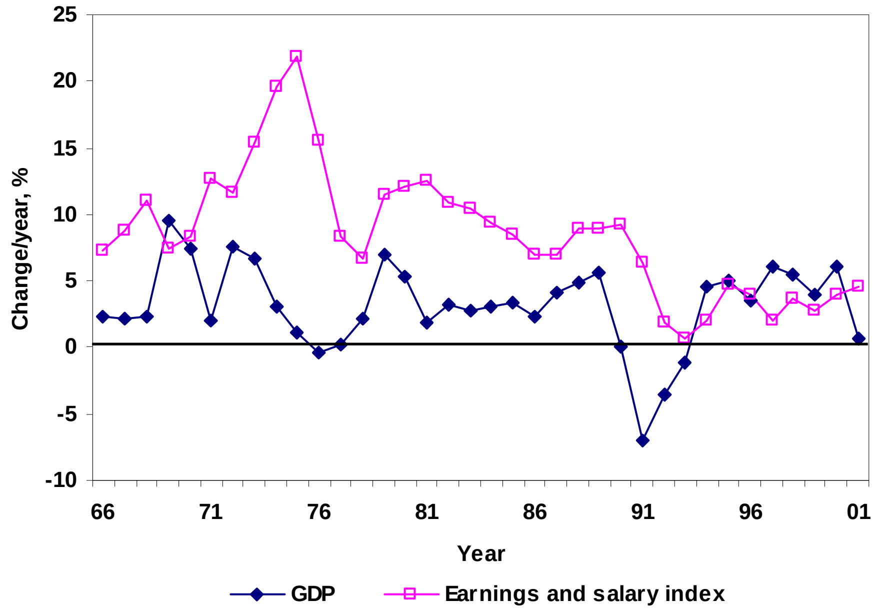
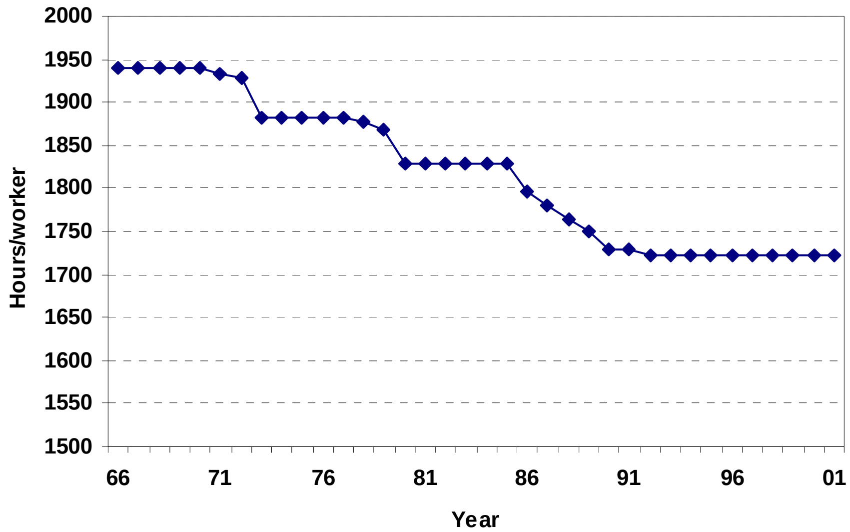
Appendix figure 1. Yearly change of GDP and earnings and salary index.



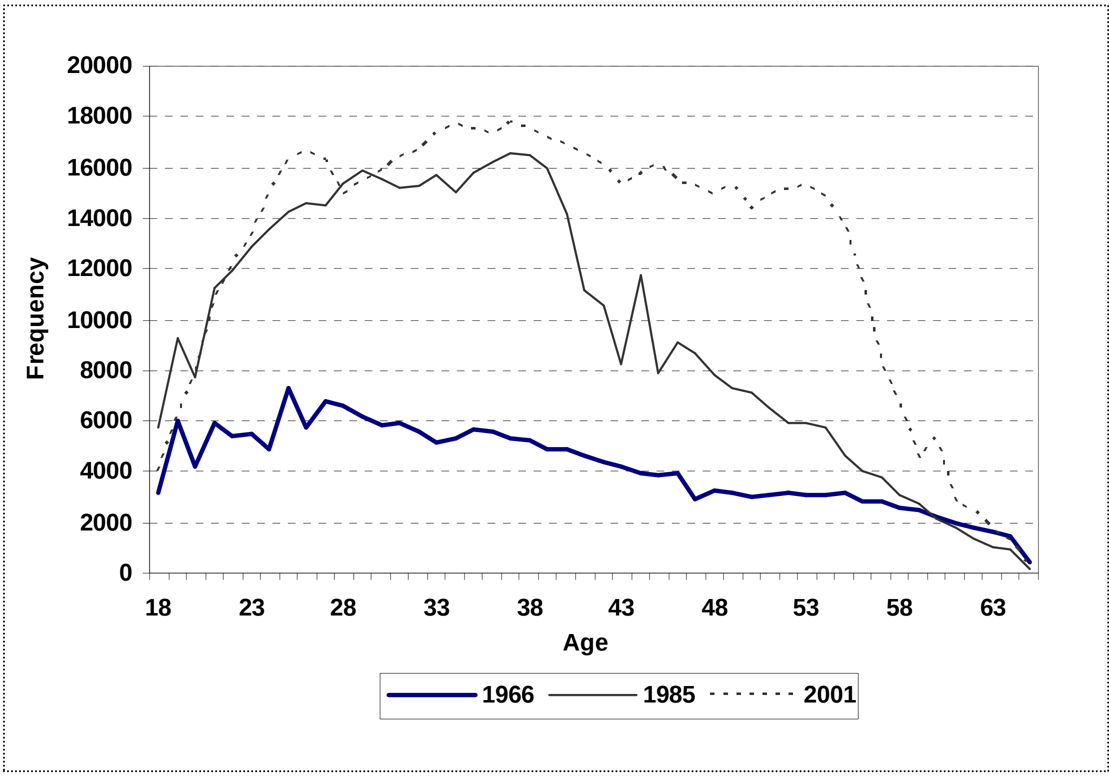
Source: Statistics Finland

Appendix figure 2. Regular annual working time, industrial worker.

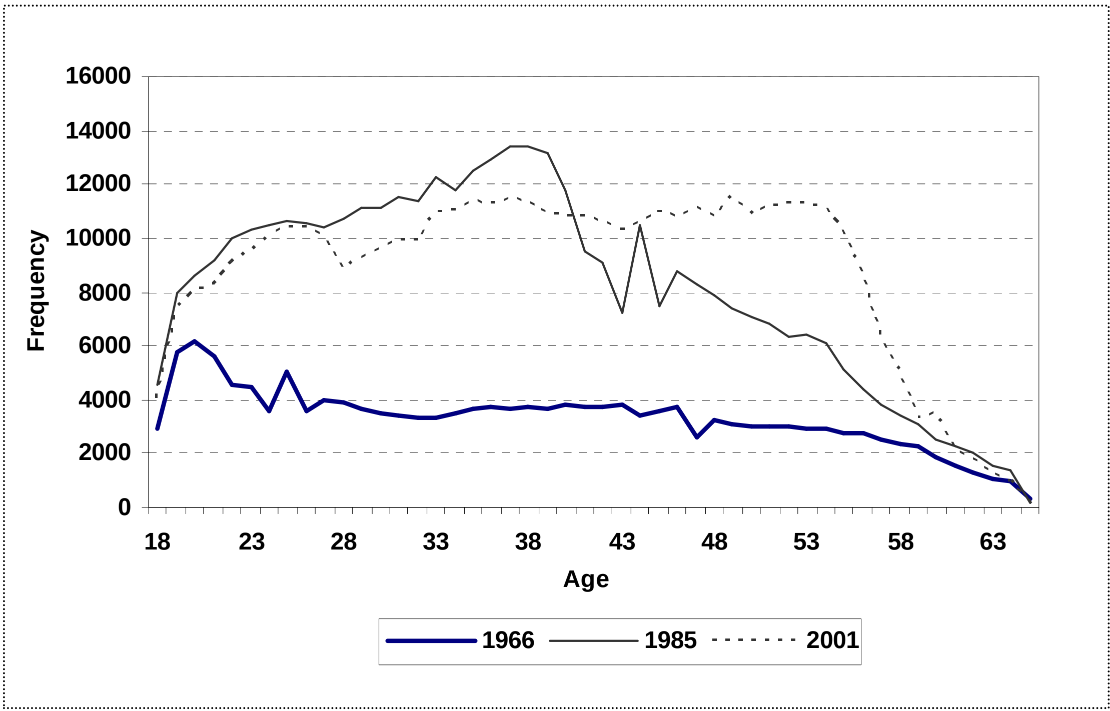


Source: Confederation of Finnish Industry and Employers

Appendix figure 3. Male population by age in the data (18–65 year olds).

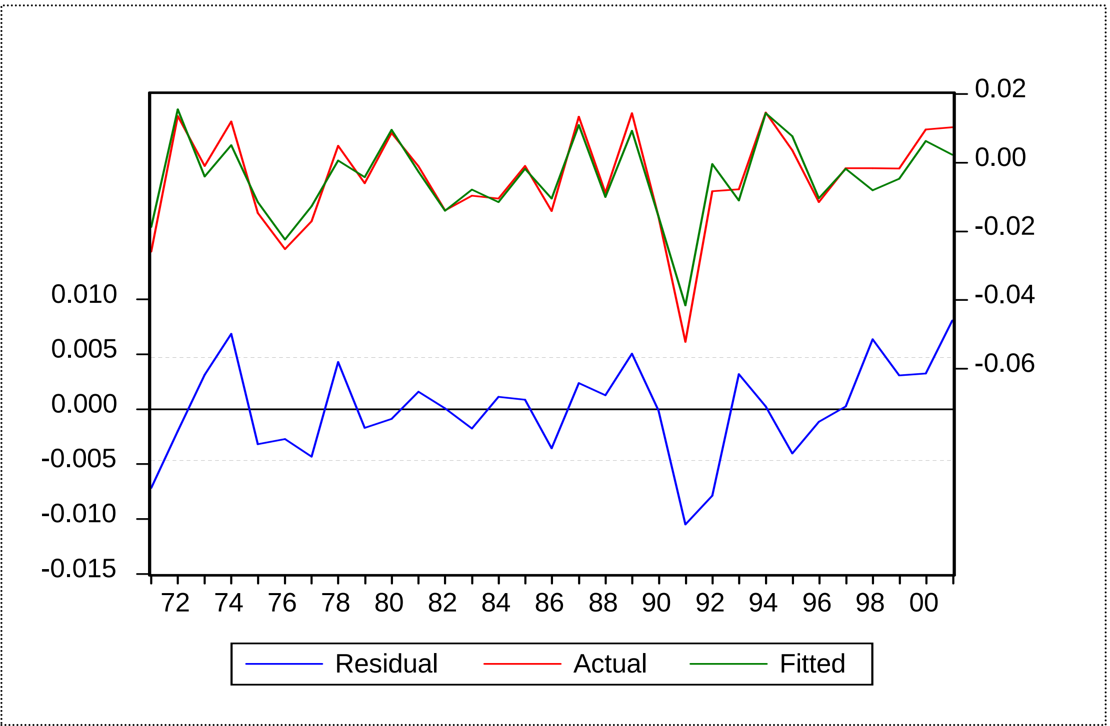


Appendix figure 4. Female population by age in the data (18–65 year olds).



Appendix figure 5. Persons insured under TEL as a percentage of the population.

Appendix figure 6. Typical realization of estimation, ARI(2,1), men 30–39.



Appendix table 1. Values of AIC for the models, men.

Model	**Men**				
	20-29	**30-39**	**40-49**	**50-54**	**55-60**
ARI(1,1,0)	**-5.55618**	**-5.92180**	**-5.49661**	**-5.38916**	*-5.43895*
ARI(2,1,0)	**-5.59122**	**-5.84431**	**-5.53827**	*-5.42212*	*-5.34207*
ARI(1,2,0)	**-5.06207**	**-4.97569**	**-4.93536**	*-4.96974*	**-4.89077**
ARI(2,2,0)	**-4.97076**	*-4.89787*	**-4.84924**	*-4.86156*	**-4.82010**
ARIMA(1,1,1)	**-5.61523**	**-6.33707**	*-5.85061*	**-5.43495**	**-5.52460**
ARIMA(2,1,1)	**-5.53846**	**-6.43166**	*-6.16733*	*-5.37374*	*-5.41799*
ARIMA(1,1,2)	**-5.57398**	**-6.38113**	*-5.74792*	**-5.37019**	~~-5.70689~~
ARIMA(2,1,2)	~~-6.85600~~	**-6.54999**	*-6.05690*	*-5.49928*	**-5.60422**
ARIMA(1,2,1)	*-5.23968*	~~-6.02555~~	**-5.15936**	*-5.30097*	*-5.18654*
ARIMA(2,2,1)	*-5.08990*	**-4.99095**	**-5.05745**	*-5.18646*	*-5.14343*
ARIMA(1,2,2)	*-5.19383*	~~-5.84288~~	~~-6.12665~~	~~-5.85274~~	~~-5.94127~~
ARIMA(2,2,2)	*-5.32081*	*-5.37280*	~~-6.22592~~	*-5.22591*	~~-5.32823~~
IMA(0,1,1)	**-5.46861**	**-5.92914**	**-5.50278**	**-5.34690**	*-5.48040*
IMA(0,1,2)	**-5.45085**	**-6.05424**	**-5.63900**	*-5.61986*	*-5.42173*
IMA(0,2,1)	*-5.32480*	~~-5.97529~~	**-5.28385**	*-5.39303*	**-5.28065**
IMA(0,2,2)	*-5.27502*	*-5.39539*	**-5.21069**	~~-5.33195~~	~~-5.47046~~

Appendix table 2. Values of AIC for the models, women.

Model	**Women**				
	20-29	**30-39**	**40-49**	**50-54**	**55-60**
ARI(1,1,0)	*-6.09156*	**-6.57481**	**-6.48639**	**-6.13695**	**-6.21682**
ARI(2,1,0)	*-5.96886*	**-6.48171**	*-6.69810*	*-6.20069*	**-6.18767**
ARI(1,2,0)	**-6.00483**	**-6.24445**	**-6.41968**	*-6.06830*	**-6.01746**
ARI(2,2,0)	**-5.96219**	**-6.30807**	*-6.37112*	*-5.97337*	**-5.90410**
ARIMA(1,1,1)	*-6.01616*	**-6.59122**	**-6.60868**	**-6.24875**	**-6.28531**
ARIMA(2,1,1)	*-6.06892*	**-6.50286**	*-6.69976*	*-6.15881*	**-6.36411**
ARIMA(1,1,2)	~~-7.17968~~	**-6.52049**	*-7.02233*	*-6.57418*	**-6.20951**
ARIMA(2,1,2)	*-5.99488*	**-6.80147**	*-7.05287*	~~-6.43784~~	**-6.29375**
ARIMA(1,2,1)	**-5.93142**	**-6.94956**	*-6.39639*	*-6.09220*	**-5.94964**
ARIMA(2,2,1)	**-5.88532**	~~-6.37074~~	*-6.29064*	*-6.06959*	**-6.21570**
ARIMA(1,2,2)	~~-6.49207~~	~~-6.98449~~	*-6.59614*	*-6.20767*	**-6.14530**
ARIMA(2,2,2)	*-6.21428*	~~-6.85002~~	*-6.44687*	*-6.11783*	**-5.89726**
IMA(0,1,1)	*-5.96250*	**-6.44821**	**-6.07958**	**-6.04234**	**-6.10030**
IMA(0,1,2)	**-6.05947**	**-6.47292**	**-6.87351**	*-6.35454*	**-6.13953**
IMA(0,2,1)	**-6.23504**	**-6.49178**	**-6.30765**	*-6.16634*	**-6.16328**
IMA(0,2,2)	**-6.22779**	**-6.49827**	**-6.67165**	*-6.03087*	**-6.13352**

Note: Cross out indicates that the model has been dropped because of lack of significance or other problems. Italics indicate that the model has been dropped because of over 5% error. Bold indicates that the model has been ac cepted for further analysis.