Age-Wage Profiles for Finnish Workers

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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?

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Traditionally income studies have been based on individual data, but our data consist of aggregate-level information. It can be seen that age-income profiles have changed dramatically over last four decades in Finland (Figure 1, next page). 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 younger generations. Another interesting question is women's wages. Will women catch up with men in the future wage development? We try to find answers to these questions from our data, by using time-series methods to predict wages in the near future.

The data available to us are somewhat unique. They cover the period from 1966 to 2001 and give a nice cross-section view of the last decades with fluctuations of the economy and demography. The data covers roughly 70-95 % of the wages of people aged 15-65 insured under TEL (the Employees' Pensions Act) in the pension insurance companies. The wage concept is the annual wage that the employer reports to the companies and shows the end-of-the-year situation. The number of

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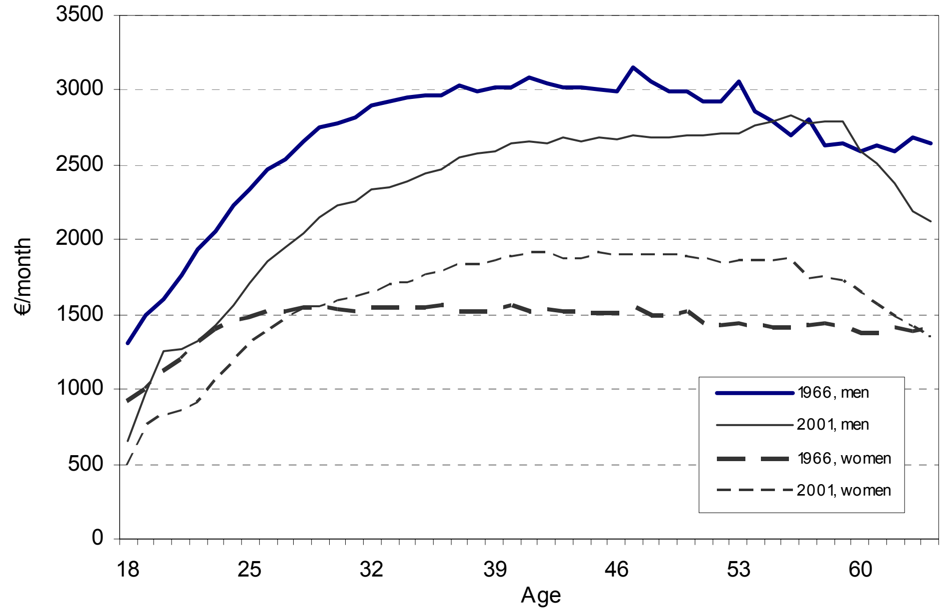
Figure 1. Age-income profiles by gender in 1966 and 2001.Data



insured has grown from 350 000 in 1966 to over 1 million in 2001. The number of women in relation to the number of men has been very stable, which is notable since women usually work in the public sector, and public sector employers are not included in our data.

However, the data have their deficiencies. There is no additional information on the underlying 'work effort' so one can not say much about the working hours. In general, working hours have decreased constantly during the period 1966 to 2001 and is currently near the EU average. 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'.

Data transformations

Before we begin to analyze the data and build models, we must look at some issues concerning data transformation. First, there is the question, how to make our data real in values? Indexation can be done in several ways, but we chose to make the data real in values by using earnings and salary index (ESI). With ESI 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 more about the question of index, see Elo & Salonen (2004).

Second, 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. Usually indexed economic data are trend-stationary, but unfortunately our data were not. We tested the stationarity of our variables by the Augmented Dickey Fuller test and found that our data should be differenced once to achieve stationary. For more detailed discussion and results of testing stationarity, see Elo & Salonen (2004).

The structural changes during our data period

Our data cover over three decades, from the late 1960's to 2001. During this time many economic and structural changes have affected the data. Some of them show in the data and some should be taken into consideration when evaluating the results. For example, the recession in Finland in the beginning of the 1990's made part-time jobs more permanent phenomenon, especially for younger generations.

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. 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, but 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, but 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 (2000)). It can partly be explained by the fact that part-time jobs are more common for women. The gender cap 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. In our data the female/male-ratios are 63% (1979), 66% (1989) and 69% (1998). The difference between men and women is bigger than usually measured in Finland (about 80 %). It can be explained by the fact that in our data men and women probably have different occupations, and their working hours differ. In the future population ageing may produce strong demand for female labour, but it will be seen if this is truly reflected in wage development, because women usually work in occupations where productivity of the worker is low. Another recent phenomenon affecting women's wages 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.

Based on this information from the data and its past behaviour, our target is to find one or more suitable models and predict age-specific wages in the future, for men and women separately.

Forecasting

In practice, predictions are almost invariably made with estimated parameters only. To build a model using all possible information and to find out the relevant variables for forecasting, we first estimated some time-series models with regressors, i.e. previous yearly changes of wages and GDP. We found models with good fit, but the problem was that we could not use them for forecasting because that would have required forecasts of the future yearly changes in wages. In addition the GDP variable turned out to be insignificant, so we decided to elaborate pure time-series models. That means we tried numerous variants in the AR, MA and ARIMA families. The theoretical background and formulas of simple linear time-series models is described in Box & Jenkins (1976). 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 Holt's method is discussed in more detail in Makridakis et al. (1998).

In determining the best models for forecasting the future we followed commonly used method of firstly doing in-sample forecasts, in which case we could study the performance of our models against observed data. The best models are then chosen and used to predict future, which in our case means years beyond 2001.

In-sample forecast 1994-2001

As said above, in-sample forecasting is a useful way to 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 began with a wide range of models. The prediction accuracy in the end determines which models will be accepted for out-of-sample forecasting. Our basic objective is to see how closely the forecasted model tracks its corresponding data series. There are several ways to measure the forecast fit. We chose one common measure; root-mean-square percentage forecast error (RMSPE). 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. We limited the number of models with the following criteria:

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

These constraints excluded some models, but still a lot of good candidates were available. Evaluating the information criterions did not help much in our case since those values were so close to each other that no evaluation could be based on them (for detailed tables about AIC values of different models, see Elo & Salonen (2004)). As a sidetrack it can be noticed that the Holt & Winters method worked well against time series models, especially for women.

In addition to facing the problem of how to pick up one best model, we also found out that a forecast based on one model only would be problematic, because we could not find one model suitable for all ages. To reduce the error caused by wrongly chosen model we decided to combine forecasts. The idea came from Makridakis et al. (1998). We followed simple methods as suggested for instance by Chatfield (2000). In fact some empirical studies show 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. 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.

Out-of-sample forecast 2002-2006

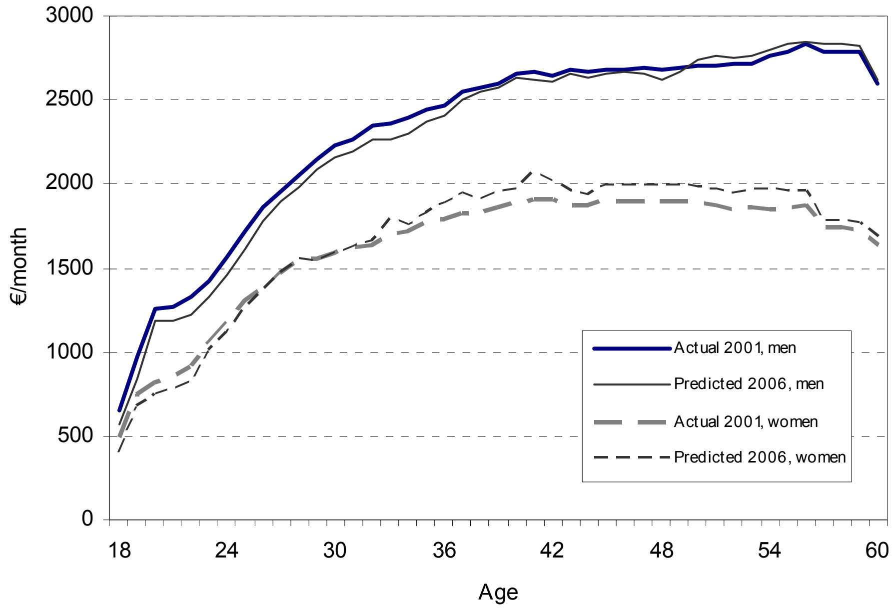
Forecasting performance for the period 1994 to 2001 was the basis for the model selection criterion for forecasting future wages. After that parameters were re-estimated for the sample 1966-2001. We included in our analysis the ages from 18 to 60, because outside these ages there were too few people to get reliable results. We found out, that the results varied quite a lot, depending of the chosen method of combining. That is because there was quite large variation between forecasts produced by different ARIMA-models. Based to that fact we decided, that median would be the best method to combine our out-of-sample forecasts. As can be seen from figure 1, the cross-section profile has changed over the years. Figure 2 shows, how this development would continue in light of our median forecast. From that figure can be seen that there are the ages of drop and the ages of growth in wages. According to our forecast for men the drop will continue between 18 and 50 years, but older men will gain in wages. For women this story is different, we expect some growth for women older than 30 years old.

Reader 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. However, we do not elaborate on that issue here.

The chosen forecasting period here is quite short, only few years. That is because simple linear ARIMA-models like ours, with a few parameters, have their limitations. They can extrapolate only the latest development of stationary time series. So they can be used to forecast only a few steps into the future, because the memory content of the model does not extend much further than that. Of course projections far away could be done, but their quality would be very doubtful.

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 some of the forecasts explode to unlikely values. This is one reason to combine forecasts. Finally, it must be kept in mind that these phenomena are subject to structural issues in the labour market. Forecasts show what could happen, if the existing conditions did not change. However, we think it is possible that some changes especially in the young age groups are about to happen. That would change these profiles notably.

Figure 2. Age-income profiles by gender in 2001 (actual) and 2006 (median forecast).



A preliminary test

The year 2002 is our first out-of-sample forecast year, so it is now interesting to compare our median forecasts for year 2002 to the actual data. Since we were forecasting real values (2001 level) it is necessary to adjust market-level wages of 2002 to the level of 2001. It is here done with the earnings and salary index change of 3.5 % from 2001 to 2002.

Zero is the reference level for a perfect forecast. The comparison shows, that there is typically some overestimation in some ages for year 2002, especially for women. It seems that our median forecast is too optimistic, compared to the adjusted market-level wages. In average, our forecast predicts roughly one per cent higher monthly wages for men and correspondingly two per cent higher wages for women.

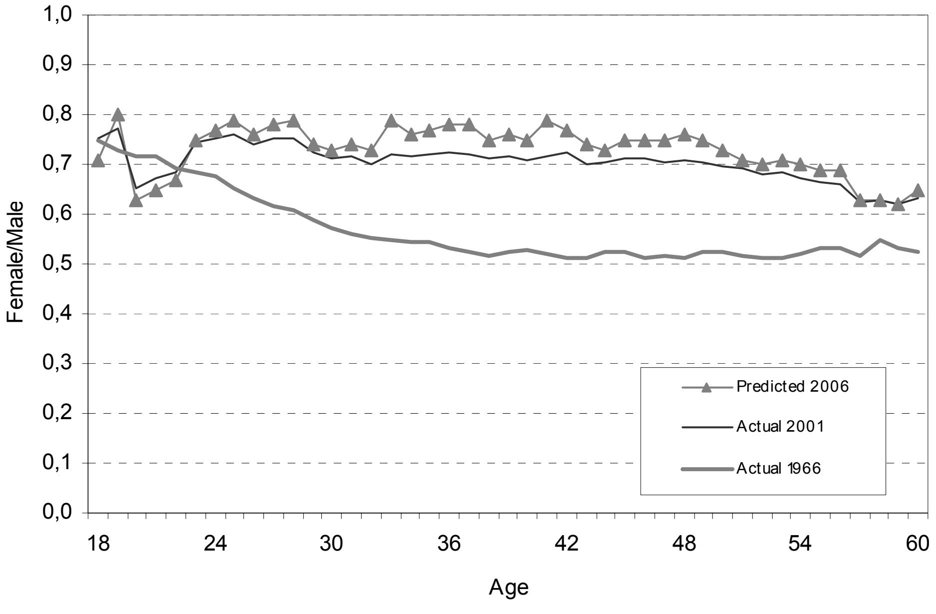
Male-female wage difference in the future

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? The result of our forecast is shown in figure 3. It indicates that the gender cap is still narrowing in the future.

Again these results are based on our median forecasts. In this we simply divide women's wages by men's wages. It seems possible that in all age groups the development we have seen in past decades will continue in the near future (See predicted line in figure 2). 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. In the official statistics the wage differ-

Figure 3. The gender gap in wages in 1966, 2001 and 2006.



ence 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. And third, one should not confuse cohort effects here. Younger cohorts are more educated, especially women. Probably cohort studies could indicate a much faster narrowing wage gap.

Conclusion

Our study introduces 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 successfully, and reasonably simple models can be applied to different ages for both men and women. Combining forecasts could be one way to improve forecasting 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 combining methods (i.e. median, average and weighted average) are presented as our out-of-sample forecasts for the years 2002 to 2006.

Our results vary considerably, depending on gender. For women the results are uniform and the long-term trend seems to continue. A vast majority of working-age women gain in earnings growth. For men the results are very different since a majority of young to middle-aged men will phase down in the wage development. The over 50 year olds seem to be the only male gainers in our study.

As a by-product of these forecasts we calculated 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, but one should also consider the structural issues and their effects.

References

Blau F., Kahn L. (2000) Gender Differences in Pay. Journal of Economic Perspectives vol 14, no. 4.

Box G., Jenkins G. (1976) Time Series Analysis, Forecasting and Control. Holden-Day, Oakland, CA.

Chatfield C. (2000) Time-series Forecasting. Chapman and Hall, United Kingdom.

Elo K., Salonen J. (2004) Age-Wage Profiles for Finnish Workers. Finnish Centre for Pensions Working Papers 7.

Makridakis S., Wheelwright S., Hyndman R. (1998) Forecasting. Methods and Applications. Third edition. John Wiley & Sons, USA.