Modeling and Predicting Individual Salaries: A Study of Finland's Unique Dataset

Lasse Koskinen
Insurance Supervisory Authority
P.O.Box 449 , FI-00101 Helsinki, Finland
lasse.koskinen@vakuutusvalvonta.fi, tel: +358 9 4155 9550, fax: +358 9 4155 9610

Tapio Nummi
University of Tampere, Finland.

Janne Salonen
The Finnish Centre for Pensions.

This paper models wages by exploiting a unique Finnish dataset. For both genders the data is divided into four income quartiles. A panel data model is estimated with the three degree polynomials of age, the duration of employment, and GDP growth as explanatory variables. Individual variation within a wage quartile is shown to be large and an important risk factor. The model provides predictors also for individual wages. Note that common salary models permit analysis only of average levels. The estimation period is 1975-1985. Genuine out-of-sample predictions are made first assuming a normal growth in 1986-1990, then a deep recession in 1991-1994.

According to the models, the wage formation seems to be essentially different in different wage quartiles. GDP is statistically significant only for one wage group, but still the prediction accuracy is remarkably worse during the recession period when GDP drops. The prediction errors for the middle-wage quarters seem to be considerably smaller than for the low and high-wage groups. There is some indication that the middle quarters can be predicted quite accurately several years ahead. The results show that individual aspects and the wage group play a significant role in modeling and prediction. This is potentially useful information when designing and developing pension schemes.

Keywords. Macroeconomic Risk, Mixture Model, Planning Schemes, Projection Method, Salary Risk.

1 Introduction

Actuarial models are constructed to aid in the assessment of the financial and economic consequences associated with the phenomena that are subject to uncertainty. This requires understanding the conditions and processes under which past observations were obtained, anticipating changes in those conditions that will affect future experience, evaluating the quality of the available data, bringing judgment to bear on the modeling process, validating the work as it progresses, estimating the uncertainty inherent in the modeling process itself (see Society of Actuaries and Casualty Actuaries Society, 1998). This paper contributes to this type of issues in the specific context of wage modeling and prediction.

The problem of salary projections is very old in pension insurance and different types of models have been proposed in the literature for describing average salary profiles. Shapiro (1998) provides a historical perspective of the research in the pension context. The problem was posed already in 1901 by Manly. A modern econometric aspect of salary projections and the relevance of projected salaries to pension plan valuation is discussed e.g. in Carriere and Shand (1998).

Individual profiles are rarely modeled. However, a moderate average wage is not equivalent to a moderate pension for all individuals. A balance should be found between the "social side" and the financial viability of the scheme, in particular with an evaluation of the repercussions of pension policies for the situation of individuals. Here we concentrate on individual salary models and predictions.

Clearly individual wage profiles are needed in pension system development but the modeling is often limited by lack of adequate data. For example Carrier & Sand (1998) argues that the challenges surrounding the projection of salaries are numerous, one being the challenge that employers do not easily volunteer salary data. Bone & Mitchell (1997) presented a strong case for obtaining more data and constructing better models of retirement income elements, so that actuaries can make better estimates and policymakers can make better choices.

Shiller (2003) also stressed the importance of good data sources. He claimed that present-day insurance and financial systems, so vital to individual well-being and social welfare, would be impossible without suitable data sources. If we are to expand the risk management institutions we will need better, more encompassing databases and data management technologies to cover these risks.

Recently empirical research in insurance has been enriched by the availability of a wealth of new sources of data across sections of individuals observed over time (cf. Plamondon et al. 2002). This provides several advantages over conventional cross-sectional or time-series approaches, facilitating the construction and testing of more realistic behavioral models. The American PSID longitudinal study is one example of how a good quality dataset can be explored in excellent fashion.

In this paper a unique dataset of individuals is exploited. It consists of all the participants of the Finnish private-sector statutory pension scheme who retired in 1998. One should notice that our data is drawn from administrative records. This means that we have no survey data issues such as PSID.

The ability to model and perform decision modeling and analysis is an essential feature of pension applications ranging from design to planning and control of systems (see e.g. Gustman et al. 1993). Models showing correlation or causality between variables can be used to improve decision-making. They e.g. can serve as an early warning system or they can be used to explore the financial effects of alternative policy options. However, modeling is fraught with dangers. A model which has been working up to now may become non-operational due to changing conditions, thus becoming an inaccurate representation of reality, and that may adversely affect the ability of the decision-maker to make good decisions.

Almost all policy decisions are based on prediction. Every decision becomes operational at some point in the future, so it should be based on prediction of future conditions. Predicting is a necessary input to planning, whether in business or in government. The selection and implementation of the proper predicting methodology has always been an important planning and control issue for insurance companies and government agencies.

The general objective of this study is to develop a model that describes - at least in part - individual features of salary development and can be used for prediction purposes. In order to properly analyze the data and to make a satisfactory prediction, it is essential to understand the environment in which the data has been collected. In particular how the environment has changed in the past. Here we studied the Finnish case as an example. During the years 1991-1993 Finland suffered from a depression that in many ways was at least as severe as the Great Depression in the 1930s. The losses of the Finnish private-sector statutory pension scheme were reported e.g. in Koskinen & Pukkila (2002). This demonstrates how difficult it is to make predictions of the deep recession period.

Panel data models are regression type models that have been used extensively in practical application. Frees et al. (2001) demonstrated the use of panel data models through series of actuarial case studies. These case studies illustrate how a broad class of panel data models can be applied to different functional areas and to data that have different features. Here we model panel data of salaries of several wage-earned categories by a mixed linear model. The parameters contain both fixed and random effects (cf. e.g. Pinheiro & Bates 2000, Nummi & Möttönen 2000).

The data was therefore divided into eight subgroups - both sexes and income quartiles. We believe the issues we explore here call for such judgment sampling since interesting features arise from examining the data in these subgroups**.** For pension applications see e.g. Pries (2005). Distributional effect is valuable information over cohort averages, which are the basic measures in pension expenditure modeling (see e.g. Biström et al. 2005). The basic fact is that incomes are not normally distributed in the target population. We may rather consider the distribution as a mixture of several subpopulations. It is very natural to assume that genders are treated as different subpopulations, but also other factors should be considered. Our approach is to further divide the data according to income quartiles in the year 1975. This can roughly be assumed to reflect the effect of certain socio-economic factors, which are rather difficult or impossible to measure on the basis of our data.

As will be demonstrated the analysis of income quartiles provides new and interesting insight into developments in earnings segments. As a special case we examine wages in the recession period. It seems that in the Finnish case the wage development was quite different between income quartiles during the recession period. Each category was modeled by a linear mixture model. These model specifications enable predicting future salaries on individuals given past salaries on the same and other individuals.

The presented models are potentially important for pension plan design and pension system development since nearly all decisions must be based on quantitative predictions (Plamondon et al. 2002). Examples of how the models can possibly be exploited are the following. First, the subgroups (income quartiles) provide more insight over averages. Many pension accrual models operate on average terms, but information on the individual income is needed for planning purposes to study individual aspects. This is essential in statutory schemes like that in Finland. Second, the wage formation seems to be essentially different in different wage quartiles. Better forecasts may be obtained by using quarter-specific models. Third, individual variation is an important risk factor and the proposed statistical models provide individual predictions. Fourth, the models further demonstrate the difference between the wages of men and women, and the fact that women are slowly narrowing the wage gap to men in Finland. We believe this is the case in other Nordic countries as well. The narrowing gender gap could be useful information when one is modeling or forecasting pension accrual.

The paper is organized as follows. In Section 2 a panel dataset consisting of individual wages is evaluated. Section 3 models panel data of salaries of several wage-earned categories by a mixed linear model, and the prediction power of the model is analyzed in Section 4. The final section concludes and discusses.

2 Individual salary data

The data was collected as a part of the Finnish pension reform package in 2001-2002 (www.etk.fi / Pension reform 2005). The unique dataset consists of all people who retired in 1998. Pension companies and institutions provided the data with individual yearly wages and working time, and some background information such as date of birth and sex. The working hours data is recorded daily and is of good quality. This enabled us to calculate the effective wage by dividing monthly wages by the work effort. The yearly working hours are also used as an indicator for career integrity. The duration of the career is used as an explanatory variable for wages. The whole panel of data consists of a group of people, whose information we have from 1975 to 1994. However, we restricted the data according to our needs.

Since our data is drawn from official administrative records, we do not have to worry about survey data issues (see for example Little & Rubin, 2002). The dataset is complete, with very few errors or other missing-data mechanisms, because the future pensions are based on the data. Naturally there are limitations in the contents. The key limitation is that we have no further information which could be used as an explanatory variable.

The first restriction is that part-time workers are excluded, limiting analysis to those who had spent their careers in relatively stable jobs in the private sector. In the dataset 86 percent of men and 71 percent of women had earnings records for the whole period covered. The second restriction follows from the fact that the data consists of those who retired in 1998. Because of the previous fixed-age pension scheme this peaks in some cohorts. Here the peak cohorts were born in 1933 and in 1938.

Bearing these facts in mind we focused on the cohorts born between 1933 and 1938 (see Figure 1) and the years from 1975 to 1994. These limitations mean that we have 2986 individuals in the analysis. There are 57% women and 43% men in the dataset. The difference in wages between men and women is illustrated in Figure 2. One should notice three issues here. First, the wage difference is quite substantial in our data. It varies between 55 and 66 percent, which is somewhat more than expected. Second, the wages have developed differently for men and for women. Women have been raising their wages (actually their wages have grown faster than the salary index) and men's wages have slightly decreased. We do not elaborate this issue here, but it seems that the wage gap is narrowing in Finland. Third, the recession period began in the year 1990. It seems that the response was different for men and for women.

***Figure 1**. Size of cohorts, percentages.*

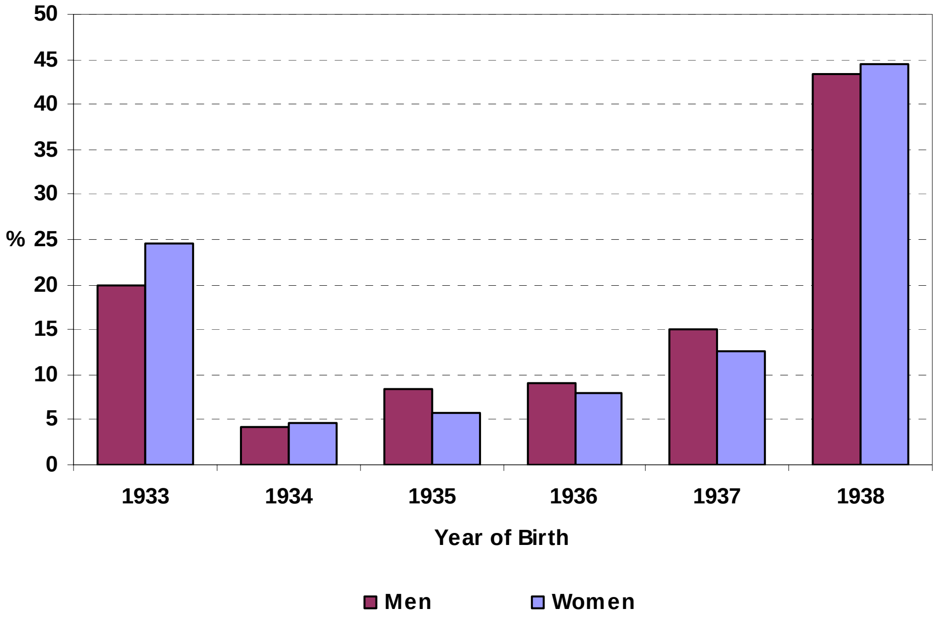
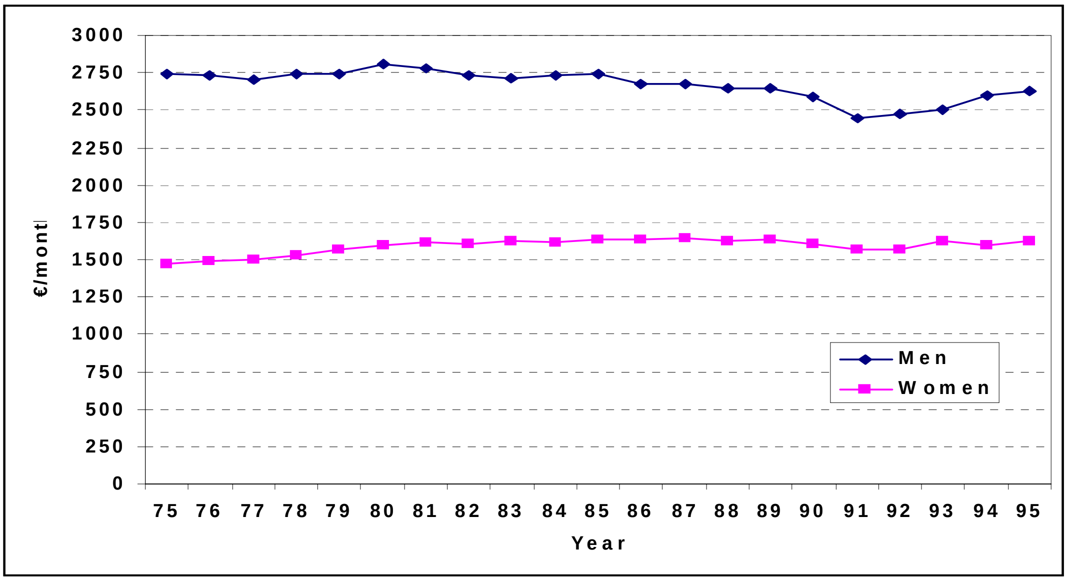


***Figure 2**. Private-sector earnings development for selected Finnish cohorts. In 1998 prices (Earnings and salary index).*



One should notice that the data here covers people of middle age. The rate of growth in wages was found to be strongly linked to the working hours in the case of the lowest quartiles for males and the two lowest quartiles for females. This is a rather expected result since the working hours for the lowest quartiles are low for both men and women.

The division of the data into income quartiles was done according to the incomes of the year 1975, when our analysis begins. In each data subset the individuals were then followed throughout the years covered by the study. From Tables 1 and 2 one can see how these quartiles have evolved. The tables show how the initial individuals of 1975 align at the year 1985 (the percentages of individuals).

Table 1. *The income quartiles of 1975 in the year 1985, men in percentages.*

	Year 1985			
Year 1975	**Q1**	**Q2**	**Q3**	**Q4**
Q1	72	19	6	3
Q2	29	46	19	6
Q3	8	27	42	23
Q4	3	7	19	71

Table 2. *The income quartiles of 1975 in the year 1985, women in percentages.*

	Year 1985			
Year 1975	**Q1**	**Q2**	**Q3**	**Q4**
Q1	39	35	18	8
Q2	8	36	43	13
Q3	3	9	45	43
Q4	1	2	12	85

Several issues arise from these tables. One can see that the initial income distribution is by no means stable. People move from one segment to another, and not always to higher quartiles. This is evident for men. For women there is more movement to the upper quartiles. It seems that the majority of the people in the higher quartiles (Q3 and Q4) keep their positions over time. Women have a tendency to reach higher quartiles.

The assumption that earnings at a particular age are log-normally distributed is widely accepted. From Table 3 one can see the basic statistical measures for both men and women for the years 1975 and 1985. The data is pretty much non-normal according to the Kolmogorov-Smirnov test as statistics show. Instead the wage in each income quartile should be a good quality response variable.

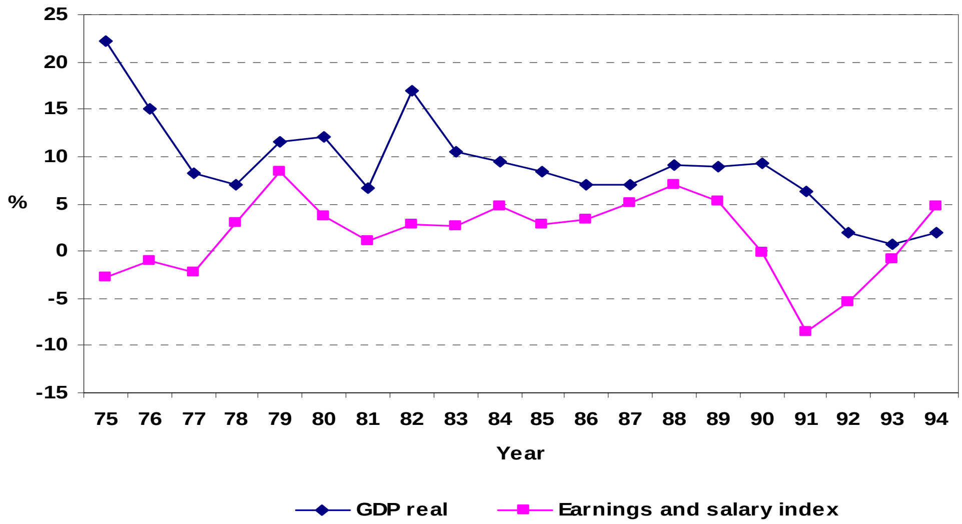
***Table 3**. Basic statistics of response variable wage at the year 1975 and 1985.*

	Men 1975	**Women 1975**	**Men 1985**	**Women 1985**
Mean	2633	1435	2592	1601
Std.deviation	1285	547	1451	622
Skewness	2.37	0.78	3.64	1.69
Kurtosis	8.12	2.02	23.33	10.72
Kolmogorov-Smirnov	0.16 (0.01)	0.07 (0.01)	0.17 (0.01)	5.86 (0.01)

The duration variable is intended to measure the integrity of the individual career. In our final data which covers the period 1975 to 1985, the duration gets values from 1 to 11. If an individual has worked a little every year throughout the period the duration gets the value 11. Our final dataset covers private-sector workers who usually work in fixed-term contracts. This means that the duration values are most often 11. It turned out that 86 percent of men and 71 percent of women had earnings records for the whole period. In this study we examine if career integrity has an effect on wages.

Since there are reasons to expect that wages tend to follow overall economic performance, GDP was introduced as an explanatory variable. The annual change of consumer price deflated GDP (1998 prices) was used here. The economic cycle is shown in Figure 3. The recession pattern is evident as GDP fell sharply between the years 1990 and 1993. In the context of non-life insurance Hartwig et al. (1997) studied workers' compensation and the economic cycle. They found a strong association between economic growth and rising frequency, severity and loss ratio.

Figure 3. Annual growth of real GDP and earnings and salary index (%).



Finally the effective wages were deflated to 1998 prices using the earnings and salary index. It is important to understand this because it puts our data and results in perspective vis-à-vis general earnings development without influence on individual careers. The response variable is also real in terms of general earnings. Using an earnings and salary index as a deflator has its merits. First, in data which is divided into subgroups one can see the difference between group wages and general earnings. Second, the pension accrual is most often (in Nordic countries) based on an earnings and salary index. The output of these calculations (individual career predictions) can be exploited in studying individual pension accrual.

The development of average wages for different male income quartiles shows a slight negative trend, which means that these cohorts fall behind general earnings. In this respect the subgroups do not provide any extra information. By contrast in percentage terms the change in wages (yearly change of response variable) varies from one quartile to another (see Figures 4 and 5). This demonstrates why separate model specifications might be needed for different subgroups.

Figure 4. *Annual change (%) of mean wage in each quartile (men).*[*]

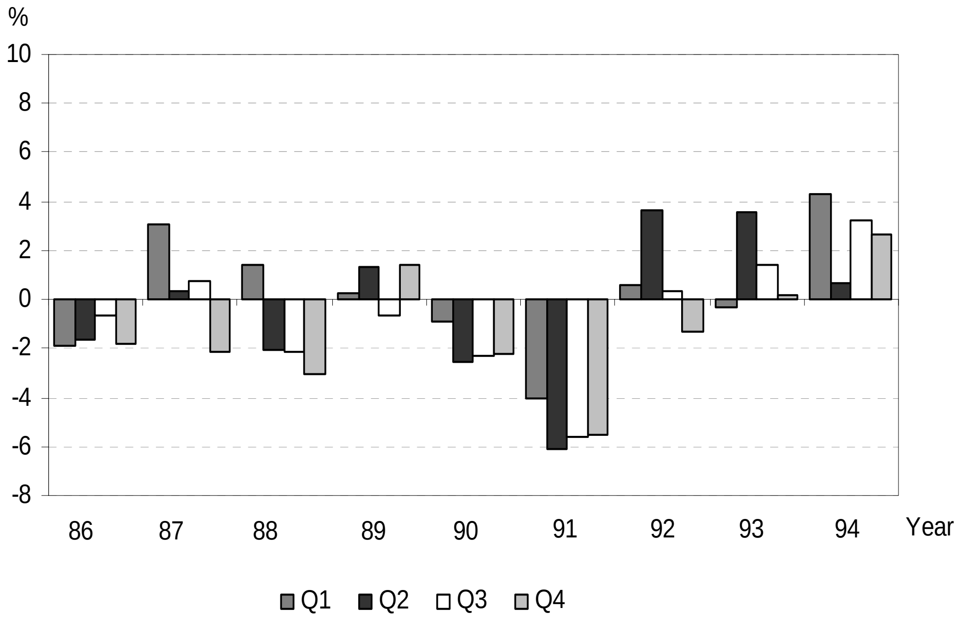
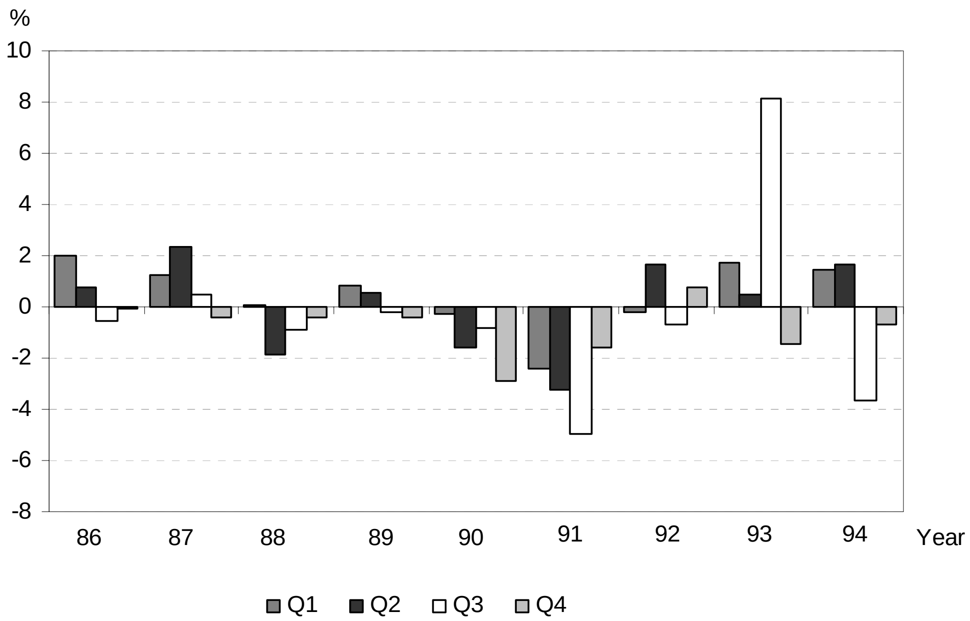


Figure 5. *Annual change (%) of mean wage in each quartile (women).*[*]



*** Q1=lowest, Q2=2nd lowest, Q3=2nd highest, Q4=highest.**

The model

The model is an extension of the basic linear model that allows some model parameters to be drawn from a probability distribution. This kind of model is usually referred to as mixed model since the model parameters contain both fixed and random effects. The following individual specific and economy-wide variables are used

- z_{ij} age of an individual i at time j
- d_i duration of the career of an individual i
- b_j the change of GDP at time j

In economics the human capital model is dominant in explaining the variation of wages over the life cycle. In short, it means that young individuals invest heavily in their schooling and job training. As a result their expected wages will rise with age as their human capital accumulates, but will eventually fall with depreciating human capital. This theory has been tested in econometric studies using suitable age polynomials. Most specifications of the earnings function include linear and quadratic polynomial terms for age. The functional form may lead to an overstated age-earnings profile (cf. e.g. Murphy and Welch, 1990; and Johnston and Neumark, 1996). Panel data allowed us to account for individual variation.

We examined a number of specifications, especially with different age variables. The conventional age and age squared are not enough, but also a cubic term should be needed. The linear mixed model we ended up with is of the following form

$$y_{ij} = \beta_0 + u_{i0} + (\beta_1 + u_{i1})z_{ij} + \beta_2 z_{ij}^2 + \beta_3 z_{ij}^3 + \beta_4 d_i + \beta_5 b_j + \varepsilon_{ij}.$$

The fixed parameters β_0 β_1 ,...,β_5 are coefficients associated with the entire subdata. The formula provides both average and individual wage predictions.

Random parameters u_{i0} and u_{i1} are associated with an individual under consideration and they can be used to model the individual specific development of a salary curve. The random errors ε_{ij} are assumed to be independently and normally distributed. Here we assume that the joint distribution of u_{i0} and u_{i1} is

- multivariate normal with the expected value zero
- independent of the random errors ε_{ij}

The estimates of the model parameters are obtained by using the so-called REML (Restricted Maximum Likelihood) method, which maximizes the modified likelihood function of the normally distributed observations. Note that REML estimates preserve the nice statistical properties of Maximum Likelihood (ML) estimates and are often prefered over ML estimates in most of the basic statistical program packages (see e.g. Pinheiro, J. and Bates, D. (2000)).

Parameters

The starting point for group-specific modeling is that the same model is estimated with every group - for each quartile (Q1-Q4) and for both genders. The estimation period covers the period from 1975 to 1985. We left the rest of the data for testing predictions. The estimation results are presented in Table 4 (more statistics can be found in Appendix A1 and A2). The results indicate that there is substantial variability both between wage groups and genders. We also tested the approach where a separate model for every wage group was estimated. Somewhat surprisingly, the fitted model specifications, especially for men, did not differ much.

The wage quartile was reflected in the model specification in a number of ways. The factors influencing the salary varied significantly between quartiles. Table 4 indicates that the quartiles have common features, but also some notable differences. A highly significant relationship was found between age (or its transformation) and wages in both genders, whereas GDP growth was statistically significant only in the case of women's quartile 2. For women the significance and effect varied from quartile to quartile. For men age had a positive effect and the square of age has a negative effect on wages. Yet the quartile-specific parameters differed markedly.

The duration of the career had a significant effect only for the lowest wage quartiles. The link with wages in other groups was much weaker. This is a rather expected result since the lowest quarters have the highest unemployment risk.

For men the cube of age was a significant factor for the two lowest quartiles. For women it was the only factor contributing in every quartile. It had a negative effect for women and positive for men (Q1-Q2).

Table 4. *Model specification for wage quartiles and genders.*

	Men	Women
Q1 (lowest)		
Age	77.9 ***	-25.9
Agesq	-2.2***	1.9**
Ageq	0.0***	0.0**
Duration	77.5***	32.3***
GDP	-39.1	-104.3
Q2 (2nd lowest)		
Age	172.9***	-31.2***
Agesq	-4.6***	2.6***
Ageq	0.0***	0.0***
Duration	8.4	11.1***
GDP	-20.1	171.0**
Q3 (2nd highest)		
Age	131.1***	-1.8
Agesq	-1.7*	2.0***
Ageq	0.0	0.0***
Duration	0.5	5.8
GDP	-95.6	39.6
Q4 (highest)		
Age	221.0***	20.4
Agesq	-2.3***	1.4
Ageq	-	0.0**
Duration	-58.7	30.0
GDP	- 70.8	-19.6

*****=1%, **=5% and *=10% significance level**
Q4: Ageq caused singularity.

A potential application of the models

At the beginning of 2005, the earnings-related statutory pensions in Finland underwent the largest reform in their 40-year history (see www.etk.fi/ Pension reform 2005). The pension reform applies to every new pension that starts after the reform has entered into force. The old system computed the pensionable wage – the base wage for all benefit calculations – for each job separately by averaging the last 10 years in each job. This procedure ignores earnings differences among workers in the other years. The new system bases the pensionable wage on all earnings and does not distinguish among jobs in different sectors of the economy. The earnings-related pension will be calculated directly as a percentage of the annual earnings.

In this kind of reform process a critical factor is to determine what kind of benefits the new system would provide to different employee groups. Furthermore, the shift in pension accrual affects individuals' welfare, and its distribution, in a variety of ways. Hence an assumption of salary development and distribution needs to be specified for the relevant subgroup. The models presented in Table 4 can be used for that purpose. For instance, the models reveal that on average the highest wage quartile fares better under the old system than under the new one, contrary to the lowest quartile. On the other hand, the wage variation is largest in the highest wage quarter, which supports the use of the new system for them. In fact this type of analysis was made during the reform, but with more traditional methods.

3 Predictions

"Don't never prophesy: If you prophesies right, ain't nobody going to remember and if you prophesies wrong, ain't nobody going to let you forget" - Mark Twain

When assessing the solvency of a scheme pension experts are mainly interested in predicting average wages. Instead, in system development, individual variation in wages is essential - a high average wage does not guarantee an adequate pension for all members of the group. Hence predicting individual salary growth is very important for planning purposes and risk assessment.

In the course of time the factors influencing the wages are subject to change and the estimated model specifications might lose their predictive power. One would expect that economic conditions are reflected in wages. However, GDP was a statistically significant factor only in one case (Q2 women). It is not unthinkable that rather than being dependent on every movement in GDP, wages react only to recessions and booms.

The model specifications presented in Table 4 were the basis for our prediction task. We show that the fitted models can be used to produce individual wage predictions as well as standard errors of estimates.

When a time-dependent model is formulated and fitted to the same data then inferences and forecasts made from the fitted model will be biased and seriously over-optimistic. Hence genuine out-of-sample prediction tests are needed (cf. e.g. Chatfield 2001). We use the models presented in Section 3. They were fitted to the data from 1975 to 1985. We test the prediction of model specifications in two very different forecasting periods. First, from 1986 to 1990 that was a "business as usual" period. Second, from 1991 to 1994 that was a deep recession period. This kind of exceptional slump in the economy is a tough test on prediction. To summarize, the estimation and forecasting periods are

- Estimation period: 1975 – 1985 (Normal economic growth);
- Forecasting period I: 1986-1990 (Normal economic growth);
- Forecasting period II: 1991-1994 (Recession);

First predictions were needed for the exogenous variable GDP - age can be predicted without problem and we assumed constant duration. Holt-Winters predictions for GDP were made. It resulted in a 2.3–2.5% annual increase in 1986-89 and a 2.6–2.7% increase in 1991-94. Figures 6 and 7 illustrate the individual variation in predictions. The duration has only a minor effect on wages except for the two lowest female quartiles. It is also very difficult to predict. Hence we assume *an integrate career* during the forecasting period.

Figure 6*. Examples of individual wage predictions and actual values (men).*

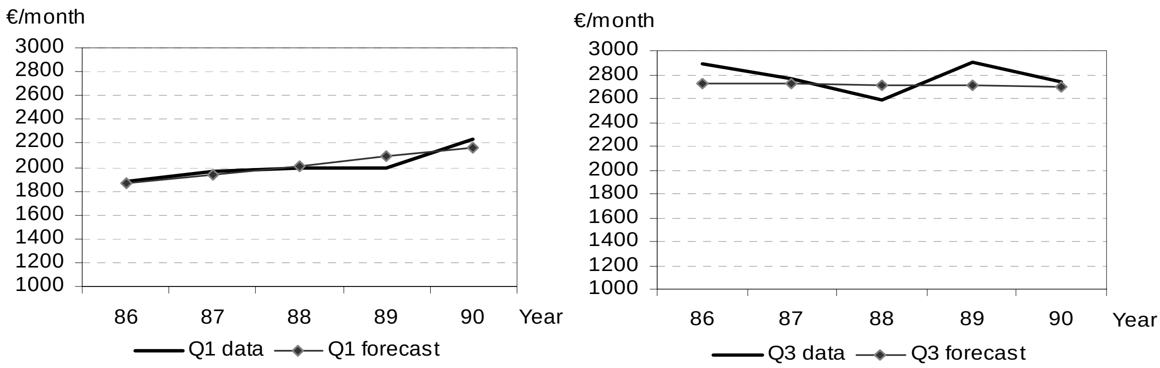
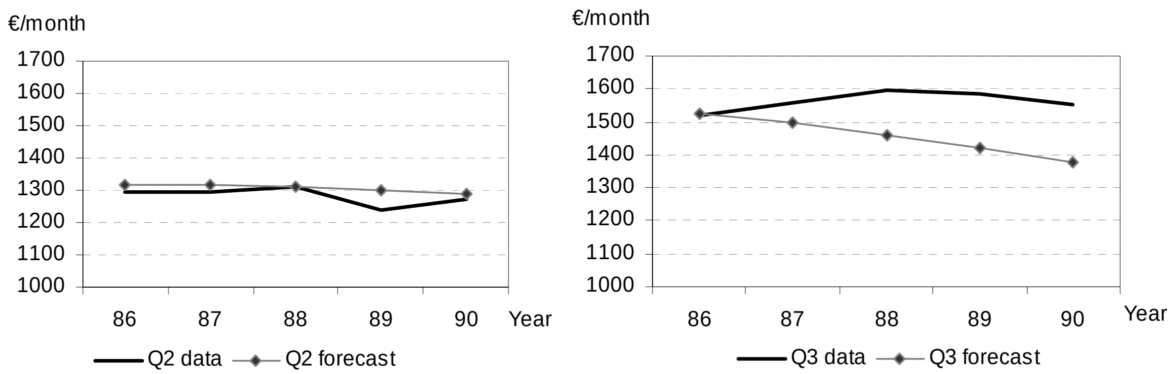


Figure 7*. Examples of individual wage predictions and actual values (women).*



Next we consider group level predictions. Figures 8–11 facilitate the prediction comparison between wage quarters and periods (more statistics can be found in Appendix B1 and B2). The errors are presented as percentages. The figures reveal several interesting features.

In a normal period (1986–1990) the models slightly overestimate the real wage development. The middle quartiles (Q2 and Q3) are well predicted. The first and fourth quartiles are rather more challenging to predict. This holds for both men and women.

Under a recession period the prediction error increases with time. This in no surprise since the Finnish recession was unexpectedly prolonged. The business cycle is certainly a factor affecting wage risk. The predictions seriously overestimate low wages. In fact, low-paid employees have difficulties in maintaining their wages. A low wage is hence associated with high wage risk. The model works very well for Q3, whose error is minimal for both men and women. The difference between men and women seems to be in the high-paid group (Q4), where the errors have different directions.

Figure 8. *Absolute prediction error as percentage of mean wage 1986-1990 (men).*

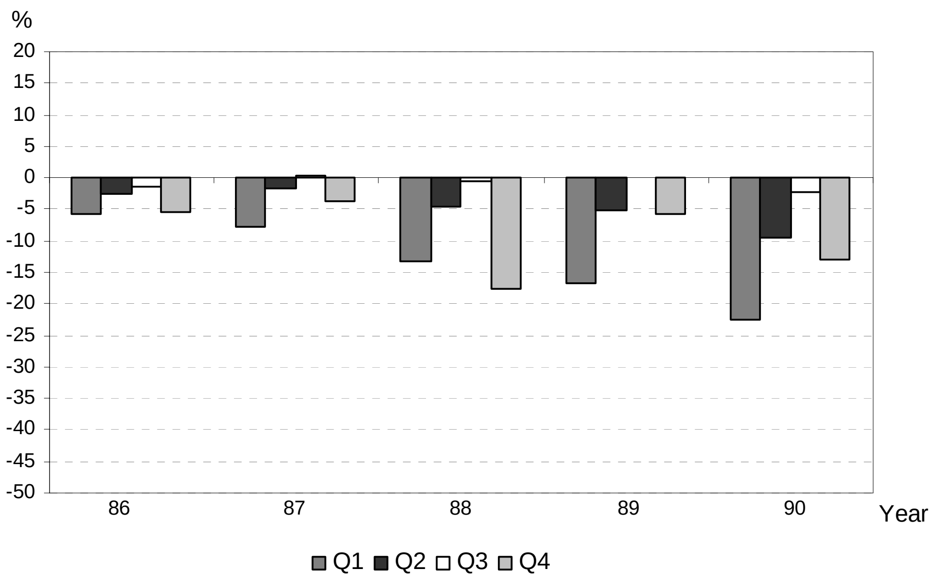


Figure 9. *Absolute prediction error as percentage of mean wage 1991-1994 (men).*

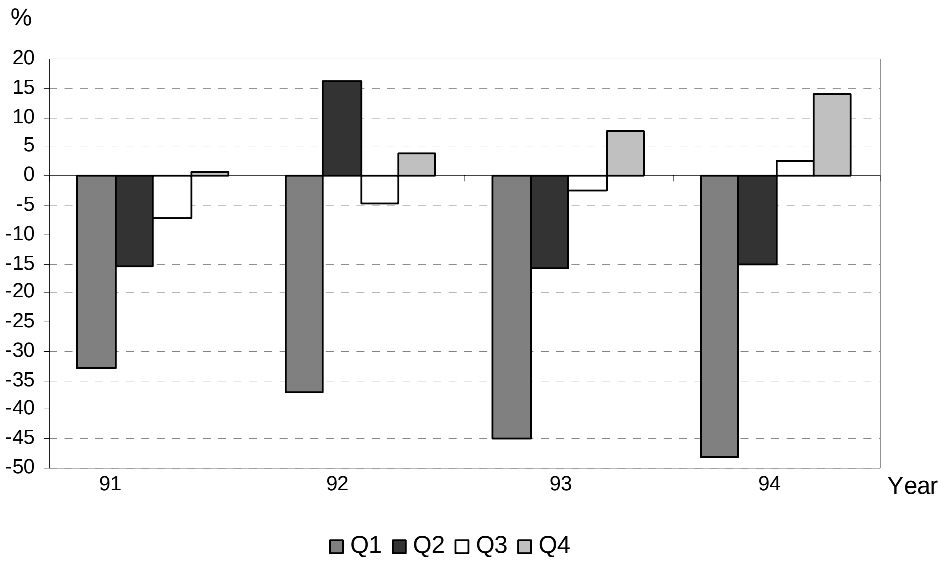


Figure 10. *Absolute prediction error as percentage of mean wage 1986-1990 (women).*

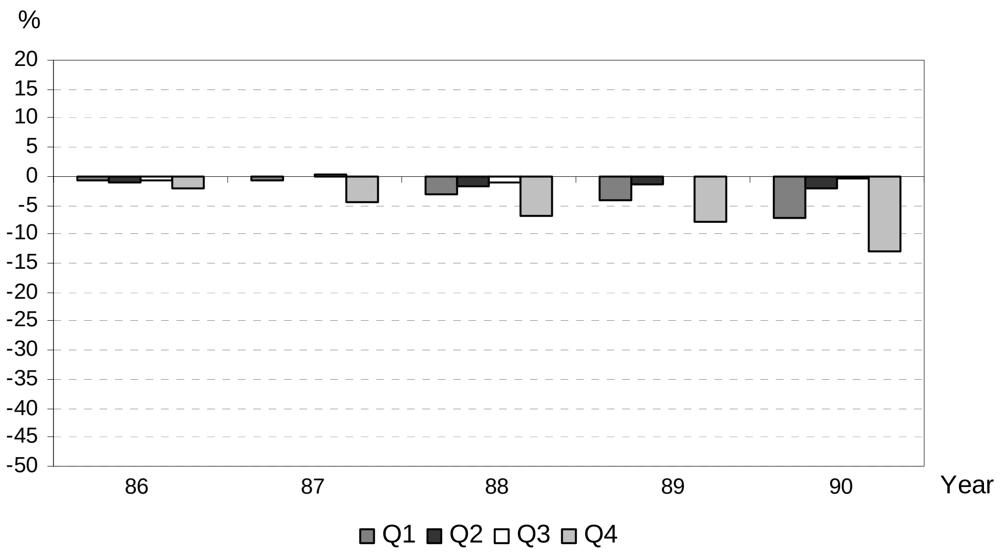
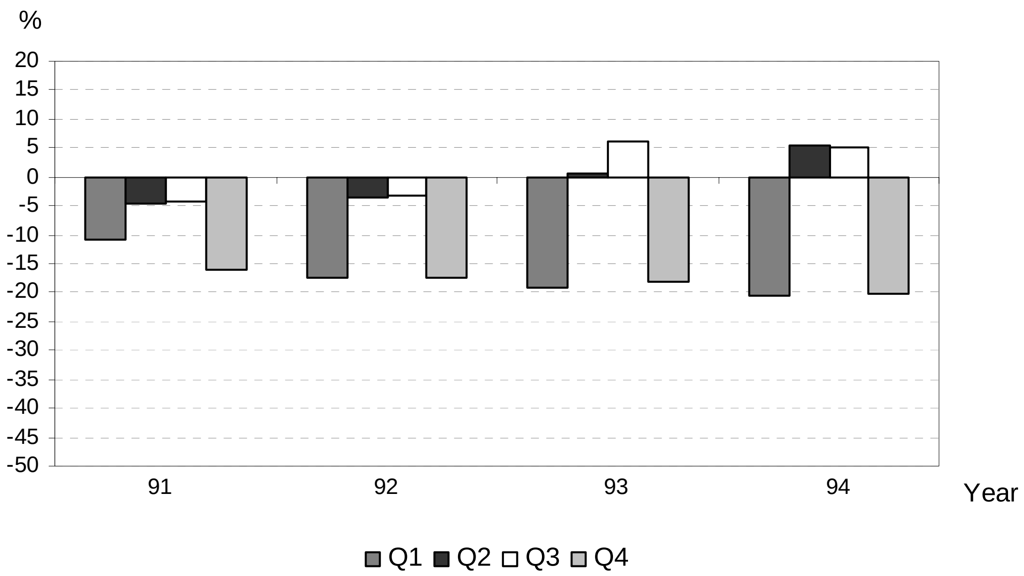


Figure 11. *Absolute prediction error as percentage of mean wage 1991-1994 (women).*



Generally one could say that these models work better for women. The figures show that the prediction errors for men are considerably larger than for women. This holds both during a recession period and during a normal period. The low-paid quartile is the most difficult to predict. One reason for this could be unemployment, which is more common in this quartile than in others. The figures reveal no clear bias in predictions. Related to the sign of the error, there are two distinct types of development. Most wages are somewhat overestimated, but for example high-paid men are slightly underestimated (Q4 in Figure 9). We think these results are an illustration that studying averages is not enough.

4 Conclusions

We have focused on the problem of modeling and predicting future salaries of individuals given past salaries. The cornerstone of this study was a dataset of individual careers, obtained from Finnish pension companies and institutions. Certain individual and economy-wide variables have been used to estimate a model for wage quartiles of both genders. The objective has not been to present all the details of the Finnish data, but to demonstrate the main features and opportunities of panel models based on high-quality data.

Modeling is never an end in itself. Here the interest has been in predicting for planning purposes. Wage forecasts may provide critical information about the pension to come and individual risk. We have studied two fundamentally different out-of-sample periods of the economy of Finland – a normal growth period 1986-1990 and a depression period 1991-1994. These predictions can be exploited in a number of pension issues.

The model specifications and prediction results allow for the following general conclusions:

- The wage formation seems to be essentially different in different wage quartiles. Better forecasts may be obtained by using quarter-specific models.
- Individual variation within a wage quartile is large and an important risk factor. In our opinion there is an urgent need to model it for pension planning purposes.
- The workers in the lowest quarter have difficulty in maintaining their wages in periods of depression. In this study the link with wages in other groups is much weaker.
- The prediction errors for the middle-wage quarters seem to be considerably smaller than for the low and high-wage groups. There is some indication that the middle quarters can be predicted quite accurately several years ahead.
- The prediction tests emphasize understanding of the economic conditions under which the past observations were obtained. For severe economic situations, judgemental scenario testing is an invaluable additional tool, because anticipating recessions is extremely difficult.

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Appendix

Appendix A1. *The parameters of the model: MEN.*

Wage Quartile 1.

	Value	Std. Error	DF	t-value	p-value
age	77.91	15.18	2581	5.13	0.00
age^2	-2.15	0.66	2581	-3.24	0.00
age^3	0.02	0.00	2581	2.62	0.00
duration	77.47	5.88	287	13.16	0.00
GDP	-39.10	141.21	2581	-0.27	0.78

Wage Quartile 2.

	Value	Std. Error	DF	t-value	p-value
age	172.94	16.45	2808	10.51	0.00
age^2	-4.56	0.70	2808	-6.41	0.00
age^3	0.03	0.00	2808	4.81	0.00
duration	8.41	7.73	287	1.09	0.28
GDP	-20.08	146.40	2808	-0.14	0.89

Wage Quartile 3.

	Value	Std. Error	DF	t-value	p-value
age	131.14	22.69	2829	5.77	0.00
age^2	-1.67	0.93	2829	-1.79	0.07
age^3	0.00	0.01	2829	0.23	0.81
duration	0.52	14.01	286	0.03	0.97
GDP	-95.56	188.85	2829	-0.50	0.61

Wage Quartile 4. (Cubic term caused singularity.)

	Value	Std. Error	DF	t-value	p-value
age	220.96	35.04	2714	6.30	0.00
age^2	-2.34	0.36	2714	-5.58	0.00
duration	-58.67	55.17	287	-1.06	0.29
GDP	-70.76	449.90	2714	-0.16	0.88

Appendix A2. *The parameters of the model: WOMEN.*

Wage Quartile 1.

	Value	Std. Error	DF	t-value	p-value
age	-25.93	16.64	2773	-1.56	0.11
age^2	1.87	0.72	2773	2.57	0.01
age^3	-0.02	0.00	2773	-2.49	0.01
duration	32.33	3.64	400	8.88	0.00
GDP	-104.25	141.51	2773	-0.74	0.46

Wage Quartile 2.

	Value	Std. Error	DF	t-value	p-value
age	-31.16	9.51	3757	-3.28	0.00
age^2	2.64	0.42	3757	6.28	0.00
age^3	-0.03	0.00	3757	-6.55	0.00
duration	11.06	2.87	400	3.85	0.00
GDP	170.95	84.86	3757	2.01	0.04

Wage Quartile 3.

	Value	Std. Error	DF	t-value	p-value
age	-1.80	10.81	3899	-0.17	0.87
age^2	2.02	0.46	3899	4.33	0.00
age^3	-0.02	0.00	3899	-5.11	0.00
duration	5.80	5.27	400	1.10	0.27
GDP	39.55	93.36	3899	0.42	0.67

Wage Quartile 4.

	Value	Std. Error	DF	t-value	p-value
age	20.38	25.80	3947	0.79	0.43
age^2	1.41	0.88	3947	1.60	0.11
age^3	-0.02	0.01	3947	-2.15	0.03
duration	30.05	25.63	400	1.17	0.24
GDP	-19.57	156.03	3947	-0.13	0.90

Appendix B1. *MEN.*

Mean prediction errors for the years 1986-1990 (”Business as usual”), €.

Year	Wage Quartile 1	Wage Quartile 2	Wage Quartile 3	Wage Quartile 4
1986	-101	-57	-34	-228
1987	-143	-37	8	-150
1988	-245	-95	-15	-687
1989	-309	-110	0	-228
1990	-416	-201	-53	-499

Mean prediction errors for the years 1991-1994 (Depression period), €.

Year	Wage Quartile 1	Wage Quartile 2	Wage Quartile 3	Wage Quartile 4
1991	-606	-324	-179	24
1992	-653	-321	-109	140
1993	-802	-320	-56	272
1994	-850	-320	61	505

Appendix B2. *WOMEN.*

Mean prediction errors for the years 1986-1990 (”Business as usual” period), €.

Year	Wage Quartile 1	Wage Quartile 2	Wage Quartile 3	Wage Quartile 4
1986	-8	-16	-13	-46
1987	-8	-3	3	-106
1988	-38	-25	-16	-153
1989	-51	-21	-3	-182
1990	-91	-32	-6	-288

Mean prediction errors for the years 1991-1994 (Depression period), €.

Year	Wage Quartile 1	Wage Quartile 2	Wage Quartile 3	Wage Quartile 4
1991	-140	-68	-73	-357
1992	-221	-53	-55	-378
1993	-242	9	98	-400
1994	-267	79	89	-435