Flexicurity and wage dynamics over the life-cycle[§]

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Abstract

We investigate the relationship between the evolution of individual hourly wages over the life-cycle and flexicurity in Denmark – a combination of employer flexibility in hiring and firing, income security during unemployment and a growing emphasis on activation for the unemployed. We use 24 years of population-based longitudinal administrative data on men to model individual wage dynamics, distinguishing between a long term life-cycle profile and transitory wage shocks. We characterise flexicurity using individual membership of an unemployment insurance fund, which is voluntary (80%) and provides access to part of the flexicurity bundle of income security with activation. We find that, flexicurity is associated with lower starting-wage heterogeneity, lower growth rate heterogeneity and greater wage instability. These findings are robust across industries and occupations. While we are in general unable to distinguish a moral hazard from an adverse selection cause, robustness checks suggest that moral hazard, combined with signalling, may be the relevant interpretation of our findings.

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1. Introduction

The Danish "flexicurity" system has often been indicated as a solution to the problems of unemployment and labour market rigidity characterising Continental Europe. As is well known, in essence the system consists of generous unemployment insurance coupled with the absence of firing restrictions. Therefore, firms are free to manage labour demand to maximise profits, while an extended social safety net prevents poverty risks and preserves social cohesion.

Increasing labour market flexibility has been the goal of labour market reforms in several European Countries such as Italy and Spain. In these cases, flexibility has been achieved at the margin, e.g. by favouring the adoption of temporary employment for labour market entrants. While effective in reducing the incidence of firing costs, such a strategy may increase income uncertainty to the extent that these contracts do not act as stepping stones into stable employment, inducing segmentation in the labour market. In this context, a flexicurity-type of system has often been advocated as a mean to reduce uncertainty and welfare losses.

In this paper we look at the relationship between individual wages and unemployment insurance. There is an extensive literature documenting the disincentive effects that insurance schemes may exert on the job search process of the unemployed (see e.g. Lalive and Zweimuller 2004). While these effects are concentrated on the duration of unemployment , other studies have shown that, by allowing a longer search, unemployment benefits may favour better and longer lasting matches (Tatsiramos, 2009). The wage effects of unemployment insurance schemes are a less investigated issue. However, there are good reasons to believe that the presence of insurance for the unemployed may affect the behaviour, productivity and wages of employed individuals.

In this paper we provide evidence on the impact of the Danish flexicutity system on the dynamics of individual wages over the life-cycle. We focus on men employed in the private sector for at least 5 years during the period 1980-2003 and use population-based longitudinal administrative register data to model individual wage dynamics, distinguishing between a long term life-cycle profile and transitory wages shocks. We relate the two wage components to individual membership of the unemployment insurance scheme (UI), the backbone of the flexicurity system. Using time variation in membership status at the individual level, we are able to relate membership to changes in the intertemporal covariance structure of wages.

We find that joining the insurance scheme affects both life-cycle wages and shocks volatility. Specifically, flexicurity membership is associated with a lower dispersion of entry wages and wage growth rates relative to non-membership, the latter finding implying that wage mobility is enhanced, leading to more egalitarian wage distributions in the long run. On the other hand, wage shocks display larger volatility amongst those group of workers characterised by a larger incidence of UI membership. The result on entry wages may reflect a blurring effect of membership on other signals that the individual may carry when entering the labour market, e.g. education. Instead, the reduction in growth rate heterogeneity and the increased volatility are consistent with moral hazard. Firstly, growth rate heterogeneity is usually associated with time-varying dimensions of productivity, e.g. learning ability, and its reduction after insurance membership may mean that unemployment protection reduces the incentives to increase individual human capital on-the-job. Secondly, increased wage instability can be associated with job turnover and a higher probability of losing employment once individuals are covered by the insurance scheme. In principle, one could also think of adverse selection interpretations for these results. While we are in general unable to test moral hazard against selection, robustness checks suggest that the former may be the relevant interpretation.

The rest of the paper is organised as follows. Section 2 discusses the policy background underlying the flexicurity model and the relevant literature. Section 3 illustrates the models of wage dynamics used to investigate the impact of flexicurity, while Section 4 provides an account of the data and the estimation sample. Results are presented in Section 5 and Section 6 concludes.

2. Institutional background

Flexibility for employers to hire and fire workers and income security for the unemployed have been features of the Danish labour market since the mid 1970's. This was combined with effectively unlimited unemployment benefit duration until unemployment peaked in 1993. Thereafter introduction and tightening of time limits and activation (job search and training) requirements coincided with falls in registered unemployment through until 2007. It is increasingly recognised that the *triplet* flexibility, security and *activation* combined to facilitate low and stable registered unemployment in a Danish model of flexicurity (Andersen and Svarer, 2007). The remainder of this section details these salient features together with the wage setting context in motivation of our empirical work which contrasts wage dynamics across sub-populations differentially exposed to flexicurity.

Employment protection has been weak by international standards throughout the period. Most blue-collar workers can be laid off with very short notice, the actual length of notice depending on the labour market agreement for the occupation. Many white-collar workers and salaried employees are legally guaranteed a certain period of notice in case of layoffs according to their tenure in the position (one month per year of employment, up to a maximum of nine months after nine years of employment). There is no similar law for blue-collar workers.

There is voluntary membership of unemployment insurance funds. These are organised largely on occupational lines, run by unions, have common contribution rates and benefits are heavily subsidised through general taxation. About 70% of the labour force are members. Eligibility to benefits requires membership and employment for 12 months. In 2009 benefits were 90% of mean earnings over the previous three months subject to a maximum monthly payment of €1,800. The average production worker earning monthly €3400 faces a 52% gross replacement rate. Both earnings and transfers are taxed, but an 8% tax on labour earnings does not apply to unemployment benefits, which implies higher net replacement rates.

Social assistance is available to those without work who are uninsured or those for whom unemployment insurance eligibility has expired. The level of support varies according to family status, age and is means tested, but would typically be 70% of unemployment benefit levels.

Effective conditionality for unemployment benefit receipt was introduced in 1994. Previously passive receipt of benefits for up to seven years could be extended indefinitely by enrolment in training programmes. Activation in the form of mandatory training and job search came in after four years of passive unemployment and after a further three years benefit eligibility expired. Subsequently these time limits for passive and active period were reduced to 4+3 (1996), 2+3 (1998), 1.6+3 (1999), 1.3+3 (2000), 1+3 (2001) and 0+4 (2003). Activation was introduced for social assistance from 1998.

Unemployment insurance funds are organised along occupational lines and run by unions, but union membership and fund membership are not bundled. Union membership has been stable at around 75% of employees and coverage around 85%. Wage bargaining in the public sector has always been centralised and agreements are reached every second year. Since 2003 there has been a small element of individual negotiation. In the private sector wage bargaining was centralised until 1980. Industry-level bargaining was introduced in 1981 and by 1987 (2003) only 34% (15%) of wages were centrally bargained. There was a minimum level of firm-level bargaining at around 4% until 1993, which increased to 21% by 2003.

In sum flexicurity features most directly affect blue collars (flexibility) and the low waged (income security) post-1993 (activation). This is against a background of decentralising wage determination, especially post-1993 to the firm level.

3. Models of wage dynamics with flexicurity membership

Our interest is in assessing how individual wage dynamics are affected when individuals are covered by the unemployment insurance scheme, distinguishing between long run wage profiles and volatile wage shocks. Long term wages reflect the remuneration of individual ability, which may well be time varying say due to learning through experience. Volatile shocks reflect the exposure of individual wages to labour market fluctuations. Both wage components may be influenced by unemployment insurance, which may affect incentives to learn or job retention. Given our focus on individual-specific wage profiles, we will estimate measures of heterogeneity of these profiles around the mean. Moreover, the very concept of wage volatility requires to model the variances of wage shocks. We therefore specify a model in which individual wages are the sum of two orthogonal components, the permanent wage and the transitory wage, and derive its implications for long term-wage heterogeneity and shocks volatility. In doing so, we will refer to models developed by the well established literature on the permanent/transitory decomposition of wage inequality, which we augment to allow unemployment insurance to play a role (see Gottschalk and Moffitt, 2008, for a recent overview of that literature).

Specifically, we postulate that

$$w_{ict} = w^{P}_{ict} + w^{T}_{ict}\,; \qquad E(w^{P}_{ict})= E(w^{T}_{ic\,t})= E(w^{P}_{ict},w^{T}_{ict}) =0;\; i=1,\ldots,N;\; t=t_{0c},\ldots, T_c \qquad (1)$$

where w_{ict} is individual's i log-wage deviation from the period (t) and cohort (c) specific mean, P and T denote permanent and transitory wages, and the time span of observation is cohort specific (see the data section). In what follows, first we illustrate the baseline wages models of interest that have been used by previous studies; next, we discuss how we enrich them to allow for the impact of unemployment insurance membership.

Given our interest in life-cycle wage growth, we model the permanent component using a random growth model, which allows for growth rate heterogeneity by means of individual specific linear profiles in labour market experience EXP_{it} (see, e.g. Haider, 2001):

$$w^P_{ict}= \pi_t\lambda_c(\alpha_i+\beta_i EXP_{it}); \qquad (\alpha_i,\beta_i)\sim_i(0,0;\ \sigma^2_\alpha\ ,\ \sigma^2_\beta\ ,\ \sigma_{\alpha\beta}); \tag{2}$$

According to this specification, each individual's permanent wage is characterised by a starting wage (α_i) and a growth rate (β_i) in labour market experience (EXP_{it}). The variances of individual specific parameters (σ^2_α and σ^2_β) capture the degree of heterogeneity along these two dimensions, say due to initial ability and ability to accumulate productive skills once in the labour market. The covariance term ($\sigma_{\alpha\beta}$) is also relevant in that its sign may indicate the existence of Mincerian cross-overs (negative) or the fact that more educated individual are faster in learning on the job (positive). While the former effect could be generated by a model of on-the-job training (Hause, 1980), the latter may be the outcome of a matching model in which education acts as a signal of initial ability. Given that we model log-wage deviations within annual birth cohorts over a 24 year period, we can separate time and cohort effects and flexibly allow for them by introducing non-parametric shifters to the permanent wage process, π_t and λ_c. The permanent wage auto-covariance implied by this model is a function of the heterogeneity parameters and the non-parametric loading factors :

$$Cov(w^P_{ict}\ w^P_{ics}|EXP_i) = [\sigma^2_\alpha + \sigma^2_\beta EXP_{it}EXP_{is} + \sigma_{\alpha\beta}(EXP_{it} + EXP_{is})]\ \pi_t\pi_s\lambda^2_c \tag{3}$$

where EXP_i is the vector collecting individual observations on labour market experience.

Following previous studies, for the transitory wage we adopt a low order ARMA process, which is aimed at capturing the fact that the wage effects of shocks do not fade away instantaneously, but only after a few time periods. In particular, here we adopt an

AR(1).[1] As for the permanent wage, also in this case we allow for flexible time and cohort specific shifters. Finally, as discussed by MaCurdy (1982), we treat the process as non-stationary and explicitly model the variance of its initial condition. In sum:

$$w^T_{ict} = \tau_t \mu_c v_{it}\ ; \qquad v_{it} = \rho v_{it-1} + \varepsilon_{it} \qquad \varepsilon_{it} \sim_{it} (0;\ \sigma^2_\varepsilon) \quad v_{it0c} \sim_i (0;\ \sigma^2_0).^2 \tag{4}$$

Wage instability is captured by the variance of white noise innovations, σ^2_ε. The AR(1) parameters and the non-parametric shifters are the argument for the auto-covariance function of transitory wages:

$$Cov(w^T_{ict}\, w^T_{ics}) = \{d_{0c}\sigma^2_0 \ + d_{dc}[\sigma^2_\varepsilon + Var(v_{it-1})\,\rho^2] + d_1[Cov(v_{it-1} v_{i\,t-s})\,\rho]\}\,\tau_t \tau_s \mu^2_c \tag{5}$$

where d_{0c} is a dummy for variances in the first year of observation, d_{dc} is a dummy for variances in subsequent years and d_1 is a dummy for covariances. The orthogonality assumption in (1) implies that the total wage auto-covariance implied by the base model results from the sum of (3) and (5).

We now extend this baseline model to allow for an impact of unemployment insurance in each wage components. Let F_{it} be a dummy indicator for whether individual i is covered by the scheme in year t. We fully interact the random growth permanent component model with the membership indicator, so that its specification becomes:

$$w^P_{ict} = \lambda_c \pi_t(\alpha_i + \beta_i EXP_{it} + \gamma_i F_{it} + \delta_i F_{it} EXP_{it}); \tag{6}$$
$$(\alpha_i\ , \beta_i\ \gamma_i\ \delta_i) \sim [(0,0);\ (\sigma^2_\alpha\, \sigma^2_\beta\, \sigma^2_\gamma\, \sigma^2_\delta\, \sigma_{\alpha\beta}\ \sigma_{\alpha\gamma}\, \sigma_{\beta\delta})]$$

The two additional individual specific parameters (γ_i and δ_i) measure the difference in intercepts and slopes of the experience profile between members and non members of the unemployment insurance scheme. Note that, as discussed in the data section, essentially individuals are non-members of flexicurity at labour market entry, so that we should consider γ_i as a backward projection of a shift occurring later in the career. The

[1] We also experimented with ARMA(1,1) specifications, but encountered convergence issues which suggests lack of identification of the MA component in our data. See Baker and Solon (2003) for similar remarks.
[2] While other authors have used cohort specific variance of initial conditions, here we allow the overall process to shift with birth cohort.

second moments of γ_i and δ_i provide information on their dispersion and their interrelationship with the base intercepts and slopes. Specifically, σ^2_γ and σ^2_δ measure the extent of heterogeneity in intercepts and slopes differentials. The covariance between base intercepts and intercept shifts ($\sigma_{\alpha\gamma}$) indicates in which direction the wage profile shifts upon membership relative to its initial position. The covariance between base slopes and slope shifters ($\sigma_{\beta\delta}$) indicates whether fast tracks accelerate or slow down the wage progression after joining unemployment insurance, relative to low wage growth workers. Although other parameters of the covariance structure of long-term earnings are, in principle, identifiable (e.g. the covariance between intercept and slope shifters) we restrict them to zero in order not to overcrowd the parameter space and also for ease of interpretation. As we will see, the specified heterogeneity parameters are enough to fully characterise the variation of the wage profile associated with membership of the scheme. The permanent wage auto-covariance function becomes:

$$Cov(w^P_{ict}\ w^P_{ics}\ |EXP_i\ F_i) = [\sigma^2_\alpha + \sigma^2_\beta EXP_{it}EXP_{is} + \sigma_{\alpha\beta}(EXP_{it} + EXP_{is}) + \sigma^2_\gamma F_{it}F_{is} + \sigma^2_\delta F_{it}EXP_{it}F_{is}EXP_{is} + \sigma_{\alpha\gamma}(F_{it} + F_{is}) + \sigma_{\beta\delta}(F_{it}EXP_{it} + F_{is}EXP_{is})]\ \pi_t\pi_s\lambda^2_c \quad (7)$$

where F_i is the vector collecting individual observations on insurance membership.

Identification of the additional parameters requires individual level variation in insurance coverage over time, implying that identification is provided by individuals switching to and from the scheme over the sample period. For younger cohorts, this should not be an issue since membership typically occurs after an initial phase spent without coverage at labour market entry (see Ibsen and Westergaard-Nielsen, 2008). More problematic, in principle, is the situation for older cohorts. However, the large number of observations for each cohort used in the analysis allows us to find non negligible numbers of insurance switchers even amongst the older groups. We provide evidence on this point in the data section.

To characterise the link between wage instability and membership, we need to take a different approach relative to the one followed with the permanent wage, given that the instability parameter σ^2_ε is not individual-specific. We therefore directly parameterise the variance of white noise innovations with respect to the incidence of insurance coverage across cohorts and years, F_{ct}:[3]

$$\sigma^2_{\varepsilon ct} = \sigma^2_{\varepsilon}\, exp(\psi F_{ct}) \tag{8}$$

Since the incidence of membership varies across cohorts and time, the resulting instability parameter varies with c and t, which identifies ψ. A positive estimate of ψ would indicate a positive association between wage instability increases and the extent of coverage by flexicurity. Note that cohort and time trends in the transitory wage are already controlled for non-parametrically, so that we are confident that ψ captures the wage instability effect of unemployment insurance. Substituting σ^2_{ε} in (5) with $\sigma^2_{\varepsilon ct}$ yields the theoretical transitory wage auto-covariance function that we use in analysis. Adding it to (7) provides the total wage auto-covariance function that accounts for unemployment insurance membership, which we denote $\Omega(\theta, X_i)$, where θ is the parameter vector that contains random growth terms, AR parameters and the non-parametric shifters for periods and cohorts on each wage component, while X_i is the union of EXP_i and F_i.

We estimate θ by Minimum Distance (see Chamberlain, 1984; Haider, 2001). This is an application of the GMM: the inter-temporal auto-covariance function of wage implied by the model specified are mapped into empirical second moments of the within cohort inter-temporal distribution of wage $A_c=N_c^{-1}\Sigma_{i\in c}A_i$, A_i being the individual contribution to A_c and N_c the size of cohort c. Let $a_i=vech(A_i)$, and $\omega(\theta, X_i)= vech[\Omega(\theta, X_i)]$. The parameter vector is identified by the following set of moment restrictions:

$$E[a_i - \omega(\theta, X_i)]=0 \tag{9}$$

Details on the estimation method are provided in the Appendix .

4. Data and descriptive statistics

We use register data on gross hourly wages for the Danish labour force between 1980 and 2003. Our analysis will be concentrated on men. This is a sample selection criterion that is

[3] The approach is similar in spirit to the one adopted by Baker and Solon (2003) to parameterise the association between instability and age.

usually adopted in the literature on wage components models and is aimed at excluding the more intermittent labour force participation of women, that may inflate wages instability. We focus on prime age men, aged 21-55, who are full time private sector employees.

Given that we work with within cohort wage differentials, it is important to impose sample selection according to the year of birth. In order to have a sufficiently long period of observation, we require that each cohort is observed at least for ten points in time. Looking at the end of the sample period, this implies that the youngest cohort that we can use is formed by individuals that turn 21 in 1994, i.e. the cohort of 1973. In principle, we could reason symmetrically at the other hand of the sample period and use as the oldest group of men that turn 55 in 1989, i.e. the cohort of 1934. However, the information needed to identify labour market experience –in turn a crucial variable for the analysis—is censored for older cohorts, and the first cohort for which we have the information needed in the analysis is 1943. Thus we allow individuals to enter and exit the panel according to the age criteria even if there are valid observations for them outside the age range, inducing a rotating panel design by cohort (see Baker and Solon, 2003).

The last sample selections are related to the hourly wage variable. First we drop observations for which the wage is recorded at zero. Secondly, we "trim" the lower and upper 0.5 percent of the resulting wage distribution of each year. Next we further exclude (the remaining few) cases whose wage fall below the minimum wage. Finally, for each man, we impose the restriction of being observed with a valid wage for at least five consecutive years to ease the identification of individual wage profiles.[4] The latter restriction implies that our panel is not fully unbalanced, thus mitigating the issues that previous researchers have found with fully unbalanced designs (Haider, 2001).

<TABLE 1>

Descriptive statistics for our sample are in Table 1. As a benchmark, we also provide statistics for the overall labour force of men aged 18-65 (but for labour market experience, for which the censoring problems mentioned above applies to older workers). The estimating sample consists of roughly 810000 individuals for a total of about 12.5 millions

[4] As a way of checking results' robustness to this sample selection criteria, we estimated the main model of interest on a sample that requires only a minimum two consecutive wage observations per worker. Our conclusions, discussed in the next Section, were unaffected by the use of this alternative sample.

person-year observations. Equivalent numbers in the labour force are 1.9 millions an 19.5 millions, with the larger churning in the labour force reflecting the fact that in its case we are not imposing restrictions about the minimum number of consecutive valid observations on the wage. There are differences concerning the average age. While in the labour force average age grows by 4 years over the 24 years time window, in our sample it grows by 13 years: this reflect the fact that the cohort structure of the data implies that there are no new cohorts joining the sample during the central part of the sample period. The wage distribution is characterised by real wage growth and increasing dispersion. Average hourly wages increase by 28 percent in our sample between 1980 and 2003, while the corresponding figure is 17 percent if we look at the whole labour force. Also, the standard deviation of the distribution almost doubles in the sample, while it grows by 31 percent in the labour force. Part of these differences are due to the different age structure, which suggests that there may be heterogeneous wage growth in age or labour market experience, a feature that will play a central role in the econometric analysis. Average labour market experience grows by roughly 12 years in the sample, an absolute increase that is similar to the one in age. Finally, the table reports tabulation of unemployment insurance coverage. As can be seen this is rather high in both the estimating sample and the labour force. However, in the former case it grows more substantially during the central years of the panel and, again, the fact that there are no young cohorts entering the sample in these central years may explain the difference, see below.

<TABLE 2>

Table 2 provides an overview of the cohort structure of the estimating sample. Reading the table by column, one can have the visual impression of the patterns of presence/absence of each cohort over time, while the number in each cell indicates the percentage of workers belonging to that cohort in a given year. Cohorts from 1943 and 1947 reach the age of 55 before the end of the sample period and therefore stop contributing to the it between 1999 and 2003. Intermediate cohorts (born between 1948 and 1959) belong to the 21-55 age range for the whole sample period. Finally cohorts born from 1960 onwards turn 21 after 1980, and therefore start contributing to estimation after the beginning of the period investigated. As discussed in Section 3, the unbalanced-by-cohort panel design provides identification of time and cohort effects.

<TABLE 3>

As seen above, UI covers a substantial portion of the sample. It is important to stress that there is an age related element to the coverage status, namely individuals join either before entering the labour force, or in the first years since entry, say in their late 20s/early 30s (see Ibsen and Westergaard-Nielsen, 2008). Those statistics are cross-sectional. An alternative way to look at UI is to consider the proportions covered at least once during the sample period. Both type of information (age variation and life-cycle incidence) are provided in Table 3, which tabulates the share of individuals that have never been on the UI scheme during the sample period, by cohort. As can be seen, the impression of pervasiveness of the scheme is even neater compared with Table 1, only 4 percent of sample members did never experienced UI coverage. Moreover there is a clear variation by cohort. Specifically, younger cohorts are still in their early 30s and for some of their members the decision may be postponed at some point in the near future, after the end of the sample period.

<FIGURE 1>

As a last piece of descriptive evidence, in this Section we describe the covariance structure of time and cohort de-trended log-hourly wages, i.e. the moments that will next be analysed by means of the model presented in the previous Section. Figure 1 plots the wage variances and covariances (of order 1, 3 and 5) for selected birth cohorts. Each of the series is increasing over time, somehow reflecting the growth of wage dispersion singled out in Table 1. For each cohort, the series tend to shift downwards as we move from the variance to the higher order autocovariances, a pattern that reflects the presence of transitory wage shocks that show up in the variance but fade away the larger the width of the time interval over which covariances are estimated. Finally, we can also note a downward shift in the covariance structure as we move to younger cohorts, an effect compatible with the presence of heterogeneous growth rates in permanent wages.

5. Results

The empirical second moments of the cohort specific wage distribution have been matched to the second moments implied by the wage model using the Minimum Distance Estimator, see the Appendix. Before moving to comment the central results about the flexicurity/wage components relationship, it is instructive to look at the overall model prediction in terms of variance decomposition. This is done in Figure 2 for selected birth cohorts.

<FIGURE 2>

For each cohort the predicted total variance increases over the period reproducing the evidence from Figure 1. Moreover the patterns of predicted total variance mimic almost identically the ones of the actual wage moments, which may not be surprising given the presence of non parametric shifters by cohort and time on each wage component. It is more interesting to consider the variance decomposition implied by the model. Permanent wage inequality seems to be the driver of increasing total variance over most of the periods and for most cohorts. Wage instability, on the other hand, is rather constant, but for the end of the period, when it first decreases and then increases. Overall, the last years of increasing inequality seem to be driven by instability. It is also interesting to consider differences across cohorts. Most evidently, the incidence of instability increases the younger the cohort considered.

<TABLE 4>

In Table 4 we report the core parameter estimates for the wage model of Section 3, i.e. excluding time and cohort shifters on the two wage components, that are presented in Appendix Table A1. We start by describing results for the baseline model, i.e. the model resulting from equations (1) and (4), which does not allow for an impact of flexicurity on the wage components, whose estimates are provided in the upper panel of the table.

Parameters on the permanent component indicate the existence of substantial heterogeneity in both starting wages (σ^2_α) and wage growth rates (σ^2_β). Moreover, the two sources of heterogeneity are negatively correlated ($\sigma_{\alpha\beta}$<0): individuals who enter the labour market with high wages are also those experiencing the slowest growth over the life-cycle, and viceversa. The result is common to many studies in the literature: see

Hause (1980); Baker (1997); Baker and Solon (2003). The leading interpretation for this finding is that the negative estimate picks up Mincerian cross-overs of wage profiles, induced by –say-- investments in (generic) on-the-job training: given two identical individuals that differ only for investing in on-the-job training, we should observe their wage profiles to cross as long as the training investment has a cost in terms of initial wages and a return in terms of wage growth. The implication of these results is that long term inequality first decreases and then increases over the life-cycle, increases taking place after the cross-over. Following Hause (1980), these estimates can be used to compute the cross-over year, defined as the year in which permanent inequality is at its minimum: $t_c=-\sigma_{\alpha\beta}/\sigma^2_\beta$, t_c denoting the year of cross-over. Our estimate of the cross over year from this baseline model is 4.25 years of labour market experience, approximately one year larger than the estimate obtained by Hause in a sample of Swedish men.

Considering now the transitory wage of the baseline specification, all core parameters are precisely estimated. The estimated AR implies that the effects of transitory innovation fades almost entirely within ten years. Note also that the variance of initial conditions (σ^2_0) is precisely estimated, which illustrates the relevance of treating the process as non-stationary.

Moving to the model which allows variance components to depend upon flexicurity membership, results are qualitatively similar. Note that quantitatively, parameters are not comparable with those in the baseline model. E.g. in the baseline model σ^2_α represents the variance of intercepts for all individuals, whereas in the main model it represents intercepts variance for those who are not covered; similarly for the variance of slopes. Note also that the covariance parameter (for which we do not specify any interaction with membership in the main model) is stable –in quantitative terms-- across models. Turning to parameters that relate the permanent wage to flexicurity, we can see that the variances of the two shifters (σ^2_γ and σ^2_δ) are precisely estimated, indicating that the individual wage profile indeed changes when individuals are covered by the insurance scheme. We can understand the direction of such changes by considering the estimates of the covariances between intercepts and intercepts shifters ($\sigma_{\alpha\gamma}$), on the one hand, and slopes and slope shifters ($\sigma_{\beta\delta}$) on the other. Both estimated parameters are negative and statistically significant. Thus, both time invariant and time varying components of productive capacity become more evenly distributed once individuals are covered by the insurance scheme, because the covariances are negative. The first results indicates that the distribution of entry wages shrinks if one compares covered workers with non-covered ones. As noted in Section 3, this result should be seen as a backward projection, in the sense that it is rare to observe individuals covered by flexicurity at labour market entry. The result on growth rate heterogeneity, on the other hand, implies that wage fast tracks slow down after joining the scheme, which induces convergence in the distribution of long term wages and wage mobility.

As a way to compare the permanent wage results between the baseline and the main model, we can compute the cross-over year from the latter model. In this case, the relevant expression is t_c=-$(\sigma_{\alpha\beta}+ F\sigma_{\beta\delta})/(\sigma^2_{\beta}+F^2\sigma^2_{\delta})$, where F is some measure of the proportion of UI members. Using the average proportion of membership reported at the bottom of Table 3 (0.89) we obtain an estimate of t_c =2.22, to be contrasted with 4.25 from the baseline model. Thence, one consequence of the compression of wage profiles (in terms of both intercepts and growth rates) associated with UI membership is an increase in the mobility of the distribution of permanent wages, i.e. faster cross-overs.

Considering now the transitory wage in the main model, comparing the results with those from the baseline model shows that parameter estimates are rather stable, and the only parameter affected is the one that in the main model is parameterised with respect to unemployment insurance, i.e. σ^2_{ε}. As for the impact of flexicurity on wage instability, the key parameter is ψ, the instability shift associated with the incidence of membership. The positive estimate indicates that a higher incidence of membership corresponds to more wage instability.

These results show that while initial wage and wage growth heterogeneity narrows for insured individuals, wage instability becomes larger. The result about initial wage heterogeneity can be interpreted within a signalling framework. As long as the dispersion of initial wages reflect heterogeneity in the signals individuals bring to the labour market, our results suggest that the informative content of such signals gets diminished if heterogeneous individuals are characterised by an homogeneous observable trait, namely UI membership. Instead, results about growth rate heterogeneity and wage instability can be interpreted as the symptoms of moral hazard associated with the insurance. Being insured may weaken the incentives to care about the good insured, in this case being employed. Covered workers may for example lose incentives to acquire new productive skills on the job, which in turn would reduce wage progressions. In particular, our results suggest that such an effect should be more pronounced for individuals that, before being insured, experienced the fastest growth. Moral hazard may, in the limit, result in a job loss. This would make the employment history more unstable and result in the larger instability that we observe in the data.

There is, in principle, an alternative interpretation that may be put forward for explaining the reduction in growth rate heterogeneity that we observe for covered workers, which has to do with selection effects. One could think of learning ability as a way to ensure oneself against the risks of job loss. When workers reach the peak of learning capacity and their wage growth stops, they may think of supplementing the learning based self insurance with the publicly provided insurance scheme. Thence, it would not be the presence of insurance that weakens wage growth, but rather the expectation of a slow down in wage progressions that induces individuals to join the scheme. However, the institutional features of the scheme do not provide support to such an interpretation. Namely, as discussed in the data section, individuals tend to join the scheme by their early 30s, well before any reduction in wage growth may start occurring.

Similarly, one could think of adverse selection interpretations for the instability result, namely that more unstable individuals join the scheme more frequently relative to workers with larger employment attachment. However, it should be noted that the instability result is achieved thanks to variation in UI coverage between cohorts and time periods, not across individuals, and that heterogeneity along those two dimensions has already been controlled for in the model by the set of non-parametric shifters.

In the remainder of this section we provide some robustness checks for our findings about the links between insurance and instability, which are also informative about the relevance of selection effects.

<TABLE 5>

Specifically, we have looked in more detail at the characteristics of the insured workers. Namely, we pay attention to the fact that for some groups of workers insurance coverage may be higher because the wage is more unstable, reversing the relationship that we have in mind. We have identified two dimensions along which there may be relevant differences in the stability of the employment relationship, namely industry and occupation. In each case, we consider a binary partition of the variable of interest. As for the first dimension, we divide metal manufacturing workers from the rest of the sample, with the idea that wages are more variable in this industry because there are more performance related contracts all other things equal. As for occupation, we consider the manual/non-manual partition, with the former group being deemed the more unstable and having the more varying wage contracts.[5] In each of the two cases, we interact the binary partition with insurance coverage, and use this interaction to model wage instability, so that our model becomes

$$\sigma^2_{\varepsilon ct} = \sigma^2_{\varepsilon}\, exp(\psi_1 P_1 F_{ct} + \psi_2 P_2 F_{ct}) \tag{10}$$

where P_1F_{ct} and P_2F_{ct} denote the incidence of insurance membership in the more and less wage-stable group, respectively.

Results are collected in Table 5. Again, only core parameters are reported, while the full set of non parametric shifters is in Appendix Table 1. In each case we find that the result that instability is larger when there is more insurance coverage is not dependent on the specific group of insured workers being taken into account, which supports the robustness of our finding. Note however that parameter estimates are not comparable within each of the two groups partition, since the impacts on instability now also depend on the incidence of each partition.

6. Concluding remarks

In this paper we have considered the relationship between individual wage trajectories over the life-cycle and membership of the Danish system of unemployment insurance. We have used linked employer-employee panel data on individual wages to decompose the wage process into its permanent and transitory components and we have characterised the impact of insurance membership on each component.

We find that membership is associated with a reduction in the dispersion of entry wages and in growth rate heterogeneity that induces equalisation of the long term wage distribution. On the other hand, there is large wage instability among workers covered by the insurance scheme. While the first result can be seen a blurring effect of flexicurity membership on other signals that the individual may carry when entering the labour

[5] Due to data limitations, we could estimate this model only for the 1980-1995 period.

market, e.g. education, we interpret the two latter findings as the symptoms of moral hazard effects associated with the unemployment insurance.

Appendix: Minimum Distance estimation of the wage model

Estimation is based on the identifying moment restrictions in (9). Let $m^*(\theta, Z_i) \equiv a_i - \omega(\theta, X_i)$, be the moment function of the model, that depends on the parameter vector θ and observables in the data Z_i (wages and observed characteristics). The set of identifying restrictions can be restated as

$$E[m^*(\theta, Z_i)]=0 \tag{A1}$$

We work with within-cohort auto-covariance structures, which enable us to separate time and cohort effects (see Baker and Solon, 2003). Thus, the number of moment restrictions available depends upon both the number of time periods and the number of cohorts. Due to the revolving panel design, not all cohorts contribute to estimation for all periods, see Table 2. Let $S_c=T_c-t_{0c}$ denote the number of periods cohort c contributes to the analysis: for each cohort we have $S_c(S_c\ -1)/2+S_c$ moment restrictions. Some cohorts contribute to analysis for the whole 24 years period, generating 300 moment restrictions. The youngest cohort is observed only for 10 years, yielding 55 moment restrictions. We have $L=\Sigma_c S_c$= 6895 moment restrictions in total.

The cohort structure of the data implies that an individual will not contribute to all the L moment restrictions, but only to the ones generated by his cohort. Moreover, the (partially) unbalanced panel design means that an individual may not contribute to all the moment restrictions of his cohort, but only for the ones referring to time points in which he is actually observed. Let r_{il} be a dummy indicator for whether individual i contributes to moment restriction l. We can work with an alternative moment function whose l^{th} element is defined as $m_l(\theta, r_{il}, Z_i) \equiv r_{il}m^*(\theta, Z_i)+(1-r_{il})0$. The GMM estimator with missing moment contributions is based on the following identifying restriction:

$$E[m(\theta, r_i, Z_i)]=0 \tag{A2}$$

where r_i is the vector collecting the L observations on r_{il} and $m(\theta, r_i, Z_i)$ is the column vector collecting the L moment restrictions $m_l(\theta, r_{il}, Z_i)$. The estimator based on (A2) is consistent for provided that observations are missing at random. We note that we have two types of missing observations, between and within cohorts. The first type is artificially generated by the fact that we stack the within-cohort empirical auto-covariance function across cohorts, and there is no problem of endogenous attrition. There may be some issue of endogenous attrition within cohort. However, as pointed out by Haider (2001), in this context one likely source of attrition non-randomness would arise if moments were computed for all cohorts jointly and there were cohort effects in attrition, something that we rule out by working with within-cohort empirical moments.

The Minimum Distance estimator is obtained by minimising the following objective function

$$Q(W)= [N^{-1}\Sigma_i m(\theta, r_i, Z_i)]' W [N^{-1}\Sigma_i m(\theta, r_i, Z_i)] \qquad \text{(A3)}$$

where W is some suitable weighting matrix

Chamberlain (1984) shows that asymptotic efficiency requires weighting the minimisation problem with the inverse of the fourth moment matrix V. However, Antolnji and Segal (1996) show that the efficient estimator may be biased due to correlation between second and fourth moments. They suggest using the Equally Weighted estimator ($W=I$), and to adjust standard errors post estimation. We follow that procedure and estimate the variance as $\text{Var}(\theta)=(G'G)^{-1}G'VG(G'G)^{-1}$, where G is the gradient matrix evaluated at the solution of the minimisation problem.

Appendix Table 1: Non-parametric shifters estimates (continues on next page)

	Main model				***Model with industry-based instability/insurance effects***				***Model with occupation-based instability/insurance effects***			
	Permanent		*Transitory*		*Permanent*		*Transitory*		*Permanent*		*Transitory*	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Time shifters (1980=1)												
1981	0.9421	0.0032	0.8810	0.0046	0.9432	0.0032	0.9002	0.0048	0.9523	0.0029	1.0928	0.0070
1982	0.8581	0.0039	0.8871	0.0051	0.8598	0.0039	0.9237	0.0060	0.8847	0.0039	1.2160	0.0092
1983	0.8426	0.0043	0.8606	0.0053	0.8451	0.0043	0.9038	0.0065	0.8788	0.0045	1.2079	0.0098
1984	0.8386	0.0047	0.8270	0.0053	0.8413	0.0047	0.8664	0.0063	0.8836	0.0050	1.1548	0.0096
1985	0.8343	0.0048	0.8173	0.0053	0.8371	0.0048	0.8507	0.0060	0.8852	0.0052	1.1377	0.0095
1986	0.8256	0.0051	0.8140	0.0052	0.8285	0.0051	0.8491	0.0061	0.8745	0.0056	1.1539	0.0100
1987	0.7603	0.0062	0.8431	0.0054	0.7637	0.0062	0.8848	0.0067	0.8310	0.0075	1.2025	0.0108
1988	0.7499	0.0063	0.8086	0.0054	0.7528	0.0063	0.8475	0.0065	0.8181	0.0076	1.1750	0.0108
1989	0.7311	0.0064	0.7971	0.0055	0.7328	0.0064	0.8291	0.0063	0.8012	0.0078	1.1703	0.0112
1990	0.7350	0.0066	0.7773	0.0054	0.7357	0.0065	0.8054	0.0061	0.7993	0.0080	1.1639	0.0113
1991	0.7021	0.0065	0.7918	0.0055	0.7029	0.0064	0.8222	0.0064	0.7693	0.0080	1.1918	0.0122
1992	0.6637	0.0073	0.7991	0.0057	0.6667	0.0072	0.8376	0.0071	0.7653	0.0097	1.1552	0.0123
1993	0.6967	0.0078	0.7184	0.0054	0.7006	0.0077	0.7570	0.0069	0.7678	0.0100	1.1071	0.0116
1994	0.7070	0.0080	0.7181	0.0055	0.7116	0.0080	0.7589	0.0071	0.7648	0.0101	1.1198	0.0119
1995	0.6862	0.0078	0.6610	0.0059	0.6913	0.0078	0.6953	0.0071	0.7209	0.0097	1.1842	0.0137
1996	0.6602	0.0066	0.6293	0.0056	0.6640	0.0065	0.6679	0.0071				
1997	0.6169	0.0061	0.6575	0.0059	0.6199	0.0061	0.7066	0.0078				
1998	0.6105	0.0061	0.7189	0.0063	0.6125	0.0061	0.7801	0.0088				
1999	0.5751	0.0057	0.7604	0.0066	0.5761	0.0057	0.8346	0.0098				
2000	0.5532	0.0055	0.7980	0.0068	0.5534	0.0055	0.8822	0.0108				
2001	0.5270	0.0053	0.8335	0.0071	0.5268	0.0052	0.9250	0.0115				
2002	0.4877	0.0049	0.8401	0.0072	0.4879	0.0049	0.9457	0.0127				
2003	0.4686	0.0048	0.8484	0.0074	0.4686	0.0047	0.9684	0.0140				

Cohort shifters (1958=1)												
1943	0.6083	0.0060	0.9058	0.0099	0.6074	0.0060	0.9049	0.0099	0.6064	0.0061	0.9350	0.0097
1944	0.6258	0.0061	0.9129	0.0094	0.6251	0.0061	0.9243	0.0095	0.6245	0.0062	0.9333	0.0094
1945	0.6364	0.0061	0.9239	0.0089	0.6363	0.0060	0.9261	0.0090	0.6339	0.0062	0.9452	0.0091
1946	0.6513	0.0061	0.9293	0.0083	0.6514	0.0061	0.9389	0.0086	0.6549	0.0063	0.9393	0.0090
1947	0.6771	0.0064	0.9579	0.0082	0.6771	0.0064	0.9700	0.0085	0.6847	0.0065	0.9560	0.0089
1948	0.7092	0.0067	0.9590	0.0081	0.7095	0.0067	0.9865	0.0089	0.7187	0.0070	0.9558	0.0087
1949	0.7251	0.0071	0.9637	0.0081	0.7254	0.0071	0.9732	0.0084	0.7446	0.0073	0.9456	0.0083
1950	0.7477	0.0073	0.9483	0.0081	0.7477	0.0073	0.9712	0.0085	0.7671	0.0075	0.9338	0.0081
1951	0.7912	0.0077	0.9534	0.0081	0.7920	0.0077	0.9910	0.0094	0.8132	0.0079	0.9438	0.0083
1952	0.8210	0.0079	0.9450	0.0079	0.8215	0.0079	0.9593	0.0083	0.8476	0.0083	0.9270	0.0080
1953	0.8394	0.0081	0.9586	0.0078	0.8400	0.0081	0.9772	0.0081	0.8727	0.0085	0.9328	0.0077
1954	0.8605	0.0083	0.9658	0.0078	0.8607	0.0083	0.9861	0.0082	0.8875	0.0086	0.9553	0.0077
1955	0.9045	0.0086	0.9700	0.0078	0.9070	0.0086	0.9821	0.0082	0.9303	0.0090	0.9534	0.0077
1956	0.9385	0.0089	0.9750	0.0077	0.9401	0.0089	0.9894	0.0082	0.9503	0.0092	0.9747	0.0077
1957	0.9755	0.0092	0.9852	0.0076	0.9767	0.0092	0.9820	0.0077	0.9868	0.0095	0.9832	0.0075
1959	1.0238	0.0097	0.9951	0.0076	1.0243	0.0097	0.9919	0.0076	0.9987	0.0098	1.0085	0.0075
1960	1.0219	0.0097	1.1164	0.0088	1.0213	0.0097	1.0901	0.0089	0.9919	0.0097	0.8760	0.0082
1961	1.0376	0.0098	1.1128	0.0087	1.0385	0.0098	1.0945	0.0087	0.9772	0.0097	0.8876	0.0081
1962	1.0595	0.0102	1.1447	0.0090	1.0595	0.0101	1.1185	0.0091	0.9824	0.0100	0.9125	0.0083
1963	1.0807	0.0104	1.1625	0.0091	1.0802	0.0104	1.1368	0.0092	0.9597	0.0100	0.9464	0.0086
1964	1.1202	0.0110	1.1727	0.0093	1.1175	0.0109	1.1423	0.0094	0.9720	0.0107	0.9524	0.0089
1965	1.1436	0.0116	1.1938	0.0096	1.1412	0.0115	1.1614	0.0098	0.9715	0.0116	0.9686	0.0094
1966	1.1148	0.0116	1.2348	0.0098	1.1115	0.0116	1.2083	0.0100	0.9162	0.0123	0.9993	0.0099
1967	1.0471	0.0119	1.2948	0.0102	1.0444	0.0118	1.2620	0.0104	0.8677	0.0135	1.0297	0.0105
1968	0.9211	0.0124	1.3558	0.0107	0.9163	0.0124	1.3360	0.0108	0.7542	0.0146	1.0943	0.0113
1969	0.7638	0.0129	1.4077	0.0114	0.7635	0.0128	1.3660	0.0117	0.6686	0.0158	1.1388	0.0122
1970	0.6702	0.0137	1.4360	0.0118	0.6656	0.0137	1.4225	0.0118	0.5491	0.0217	1.2126	0.0136
1971	0.6799	0.0169	1.4345	0.0122	0.6667	0.0172	1.4141	0.0123	0.3996	0.0370	1.2821	0.0152
1972	1.3408	0.0322	1.3009	0.0134	1.3444	0.0315	1.2298	0.0139	-0.4358	0.1020	1.3600	0.0179
1973	1.4647	0.0350	1.2592	0.0159	1.4555	0.0351	1.1982	0.0162	-1.4143	0.0636	1.6920	0.0291

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Table 1: Descriptive statistics

Year	Number of observations		Average hourly wage (DKron, 2000 prices)		Standard deviation hourly wage		Age		Unemployment Insurance		Labour market experience
	Sample (N=811651)	Labour force (N=1950947)	Sample	Labour force	Sample	Labour force	Sample	Labour force	Sample	Labour force	Sample
1980	315546	727720	155.75	159.84	46.05	56.96	29.28	37.29	0.80	0.78	8.60
1981	326064	691032	155.63	159.82	44.48	54.30	29.87	37.48	0.81	0.79	9.19
1982	350632	700891	156.25	159.74	45.17	53.93	30.34	37.43	0.84	0.82	9.66
1983	376333	708137	157.75	160.25	47.00	54.98	30.81	37.30	0.84	0.82	10.11
1984	415394	745207	157.38	158.89	48.15	55.14	31.22	37.12	0.85	0.82	10.48
1985	450544	788493	162.30	162.14	50.39	56.49	31.56	36.94	0.84	0.82	10.79
1986	473543	798243	166.64	165.38	52.93	58.19	31.98	37.00	0.85	0.82	11.23
1987	483039	777219	176.58	175.12	55.89	61.63	32.43	37.05	0.89	0.86	11.65
1988	490382	755113	180.40	179.15	58.80	64.36	32.93	37.25	0.89	0.86	12.17
1989	509895	758713	181.28	179.73	60.49	65.70	33.42	37.35	0.90	0.87	12.64
1990	524817	753116	188.35	187.69	64.63	70.17	34.07	37.79	0.90	0.87	13.23
1991	540737	765650	191.50	189.93	66.45	71.42	34.62	38.02	0.90	0.88	13.75
1992	551213	757082	190.16	188.63	65.77	70.63	35.15	38.14	0.93	0.90	14.23
1993	558019	740417	182.33	181.07	65.91	70.03	35.69	38.35	0.94	0.92	14.70
1994	592607	772551	185.51	183.97	70.87	75.16	36.10	38.23	0.94	0.91	14.98
1995	606268	793444	189.13	185.80	71.06	74.63	36.81	38.27	0.95	0.91	15.53
1996	625657	826333	190.65	185.92	71.78	74.45	37.62	38.52	0.90	0.87	16.18
1997	635777	848566	189.67	183.57	71.02	72.76	38.45	38.73	0.90	0.86	16.81
1998	643997	867705	198.18	190.27	77.05	77.79	39.31	38.95	0.90	0.85	17.46
1999	639439	884157	198.63	190.21	77.82	78.05	39.79	39.32	0.89	0.84	17.84
2000	617047	899754	202.00	191.88	80.81	80.01	40.40	39.49	0.89	0.83	18.46
2001	585760	897489	206.95	195.59	84.16	82.17	40.96	39.87	0.89	0.83	19.06
2002	593564	1130168	204.99	192.42	81.78	77.35	41.73	41.01	0.89	0.81	19.80
2003	563419	1118461	200.28	187.92	80.11	75.32	42.24	41.32	0.89	0.81	20.37
All years	12469693	19505661	184.94	179.94	69.20	70.45	35.95	38.41	0.89	0.85	14.71

Table 2: Cohort structure

	Cohort born in															
	1943	1944	1945	1946	1947	1948	1949	1950	1951	1952	1953	1954	1955	1956	1957	1958
Year																
1980	5.6	6.2	6.6	6.8	6.6	6.3	5.9	5.9	5.7	5.7	5.8	5.6	5.7	5.7	5.5	5.4
1981	5.4	6.0	6.4	6.5	6.3	6.0	5.6	5.6	5.4	5.5	5.6	5.4	5.4	5.4	5.3	5.1
1982	5.1	5.6	6.0	6.2	5.9	5.6	5.3	5.3	5.1	5.2	5.2	5.1	5.2	5.2	5.1	5.0
1983	4.8	5.3	5.7	5.8	5.6	5.3	5.0	5.0	4.8	4.9	4.9	4.9	5.0	5.0	4.9	4.9
1984	4.5	5.0	5.3	5.5	5.2	5.0	4.7	4.7	4.5	4.6	4.7	4.6	4.8	4.8	4.8	4.8
1985	4.2	4.6	4.9	5.1	4.9	4.6	4.4	4.4	4.2	4.3	4.4	4.4	4.5	4.6	4.6	4.7
1986	3.9	4.4	4.6	4.8	4.7	4.4	4.2	4.1	4.0	4.1	4.2	4.2	4.3	4.4	4.4	4.5
1987	3.7	4.1	4.4	4.6	4.4	4.2	3.9	3.9	3.8	3.9	4.0	4.0	4.1	4.2	4.2	4.3
1988	3.6	4.0	4.3	4.4	4.2	4.0	3.8	3.8	3.7	3.7	3.8	3.8	3.9	4.0	4.0	4.1
1989	3.4	3.8	4.1	4.2	4.1	3.8	3.6	3.6	3.5	3.6	3.7	3.6	3.8	3.9	3.8	3.9
1990	3.3	3.7	3.9	4.1	3.9	3.7	3.5	3.5	3.4	3.5	3.6	3.5	3.7	3.7	3.7	3.9
1991	3.2	3.5	3.8	3.9	3.8	3.6	3.4	3.4	3.3	3.4	3.5	3.4	3.5	3.6	3.6	3.7
1992	3.0	3.4	3.6	3.8	3.7	3.5	3.3	3.3	3.2	3.2	3.3	3.3	3.4	3.5	3.5	3.6
1993	2.9	3.2	3.5	3.7	3.5	3.4	3.2	3.2	3.1	3.1	3.2	3.2	3.3	3.4	3.4	3.5
1994	2.7	3.1	3.3	3.5	3.4	3.2	3.0	3.0	3.0	3.0	3.1	3.1	3.2	3.3	3.3	3.4
1995	2.6	3.0	3.2	3.4	3.3	3.1	3.0	3.0	2.9	2.9	3.0	3.0	3.1	3.2	3.2	3.3
1996	2.5	2.8	3.2	3.3	3.2	3.1	2.9	2.9	2.9	2.9	3.0	3.0	3.1	3.2	3.2	3.3
1997	2.4	2.7	3.1	3.3	3.2	3.1	2.9	2.9	2.8	2.9	3.0	3.0	3.1	3.2	3.2	3.3
1998	2.3	2.7	3.0	3.2	3.1	3.0	2.9	2.9	2.8	2.9	3.0	2.9	3.0	3.1	3.1	3.2
1999	0.0	2.6	2.9	3.1	3.1	3.1	2.9	2.9	2.9	2.9	3.0	3.0	3.1	3.2	3.2	3.3
2000	0.0	0.0	3.0	3.2	3.2	3.1	3.0	3.0	3.0	3.0	3.1	3.1	3.2	3.3	3.3	3.4
2001	0.0	0.0	0.0	3.3	3.3	3.2	3.1	3.1	3.1	3.1	3.2	3.2	3.3	3.4	3.4	3.5
2002	0.0	0.0	0.0	0.0	3.5	3.4	3.3	3.3	3.3	3.3	3.5	3.4	3.6	3.7	3.7	3.8
2003	0.0	0.0	0.0	0.0	0.0	3.5	3.4	3.4	3.3	3.5	3.6	3.5	3.7	3.8	3.8	3.9
All years	2.6	3.0	3.4	3.7	3.8	3.8	3.6	3.6	3.5	3.6	3.7	3.6	3.7	3.8	3.8	3.9

Table 2 ctnd.

	Cohort born in														
	1959	1960	1961	1962	1963	1964	1965	1966	1967	1968	1969	1970	1971	1972	1973
Year															
1980	5.1	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1981	4.9	4.6	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1982	4.8	4.8	4.4	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1983	4.8	4.7	4.5	4.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1984	4.7	4.7	4.6	4.4	4.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1985	4.6	4.7	4.6	4.5	4.5	4.2	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1986	4.5	4.6	4.6	4.5	4.5	4.4	4.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1987	4.2	4.3	4.4	4.4	4.5	4.4	4.2	3.8	0.0	0.0	0.0	0.0	0.0	0.0	0.0
1988	4.1	4.2	4.3	4.3	4.5	4.4	4.2	3.9	3.3	0.0	0.0	0.0	0.0	0.0	0.0
1989	3.9	4.1	4.1	4.2	4.4	4.4	4.2	4.0	3.5	2.9	0.0	0.0	0.0	0.0	0.0
1990	3.8	4.0	4.1	4.1	4.3	4.3	4.2	4.1	3.5	2.8	2.2	0.0	0.0	0.0	0.0
1991	3.7	3.9	3.9	4.0	4.2	4.3	4.2	4.2	3.6	3.0	2.5	2.0	0.0	0.0	0.0
1992	3.6	3.7	3.8	4.0	4.1	4.2	4.2	4.2	3.6	3.1	2.7	2.3	2.0	0.0	0.0
1993	3.5	3.6	3.7	3.8	4.1	4.1	4.1	4.1	3.7	3.2	2.8	2.5	2.2	1.8	0.0
1994	3.4	3.5	3.6	3.7	3.9	4.0	4.1	4.1	3.7	3.3	3.0	2.8	2.6	2.3	1.6
1995	3.3	3.5	3.6	3.7	3.9	4.0	4.1	4.2	3.8	3.4	3.1	3.0	2.9	2.6	2.0
1996	3.3	3.4	3.5	3.7	3.9	4.0	4.1	4.2	3.8	3.5	3.2	3.1	3.0	2.8	2.3
1997	3.3	3.4	3.5	3.6	3.9	4.0	4.1	4.2	3.9	3.5	3.3	3.2	3.2	3.0	2.5
1998	3.2	3.4	3.5	3.6	3.8	4.0	4.1	4.2	3.9	3.6	3.4	3.3	3.3	3.1	2.7
1999	3.3	3.5	3.6	3.7	3.9	4.1	4.2	4.3	4.0	3.7	3.5	3.4	3.5	3.3	2.9
2000	3.4	3.6	3.7	3.8	4.0	4.2	4.3	4.4	4.1	3.8	3.6	3.5	3.6	3.4	3.0
2001	3.6	3.7	3.8	3.9	4.2	4.3	4.4	4.5	4.2	3.9	3.7	3.6	3.6	3.5	3.1
2002	3.8	3.9	4.0	4.0	4.3	4.4	4.4	4.6	4.2	3.9	3.6	3.5	3.6	3.4	3.0
2003	3.9	4.1	4.1	4.2	4.4	4.5	4.6	4.7	4.4	4.0	3.8	3.6	3.7	3.5	3.1
All years															
Total	3.8	3.8	3.7	3.7	3.7	3.6	3.4	3.3	2.9	2.4	2.1	1.9	1.8	1.6	1.3

Table 3: Unemployment insurance by birth cohort, proportions covered at least once

Cohort	U.I. %	Cohort	U.I. %
1943	87.29	1959	89.67
1944	87.73	1960	89.57
1945	88.35	1961	89.63
1946	88.88	1962	89.44
1947	89.27	1963	89.18
1948	89.53	1964	88.44
1949	89.88	1965	87.94
1950	90.15	1966	87.39
1951	90.27	1967	87.4
1952	90.1	1968	87.9
1953	90.55	1969	87.51
1954	90.46	1970	87.46
1955	90.46	1971	86.76
1956	90.26	1972	85.69
1957	90.47	1973	83.11
1958	90.03	All cohorts	89.07

Table 4: Core parameter estimates for the wages model

Baseline					
Permanent component			Transitory component		
	Coeff.	S.E.		Coeff.	S.E.
σ^2_α	0.0079	0.0007	σ^2_ε	0.0627	0.0006
σ^2_β	0.0008	0.0000	ψ		
$\sigma_{\alpha\beta}$	-0.0034	0.0001	σ^2_0	0.0337	0.0004
			ρ	0.7732	0.0008

Main model with unemployment insurance					
Permanent component			Transitory component		
	Coeff.	S.E.		Coeff.	S.E.
σ^2_α	0.1036	0.0048	σ^2_ε	0.0036	0.0004
σ^2_β	0.0011	0.0001	ψ	2.3355	0.1210
$\sigma_{\alpha\beta}$	-0.0040	0.0001	σ^2_0	0.0404	0.0006
σ^2_γ	0.1895	0.0067	ρ	0.6991	0.0013
σ^2_δ	0.0013	0.0001			
$\sigma_{\alpha\gamma}$	-0.1387	0.0052			
$\sigma_{\beta\delta}$	-0.0007	0.0000			

Table 5: Core parameter estimates for the wages model with group specific instability insurance coefficients

A) Industry based groups

	Permanent component			Transitory component	
	Coeff.	S.E.		Coeff.	S.E.
σ^2_α	0.1069	0.0049	σ^2_ε	0.0026	0.0003
σ^2_β	0.0011	0.00005	ψ_1	18.6118	1.4446
$\sigma_{\alpha\beta}$	-0.0040	0.0001	ψ_2	1.7100	0.1393
σ^2_γ	0.1909	0.0067	σ^2_0	0.0384	0.0006
σ^2_δ	0.0013	0.0001	ρ	0.6933	0.0013
$\sigma_{\alpha\gamma}$	-0.1410	0.0052			
$\sigma_{\beta\delta}$	-0.0007	0.00003			

B) Occupation based groups (1980-1995)

	Permanent component			Transitory component	
	Coeff.	S.E.		Coeff.	S.E.
σ^2_α	0.0899	0.0051	σ^2_ε	0.0026	0.0003
σ^2_β	0.0016	0.0001	ψ_1	2.5283	0.1477
$\sigma_{\alpha\beta}$	-0.0044	0.0002	ψ_2	1.4482	0.1200
σ^2_γ	0.1508	0.0076	σ^2_0	0.0325	0.0005
σ^2_δ	0.0012	0.0001	ρ	0.4934	0.0017
$\sigma_{\alpha\gamma}$	-0.1027	0.0061			
$\sigma_{\beta\delta}$	-0.0010	0.00004			

Figure 1: Wages covariances at various lags

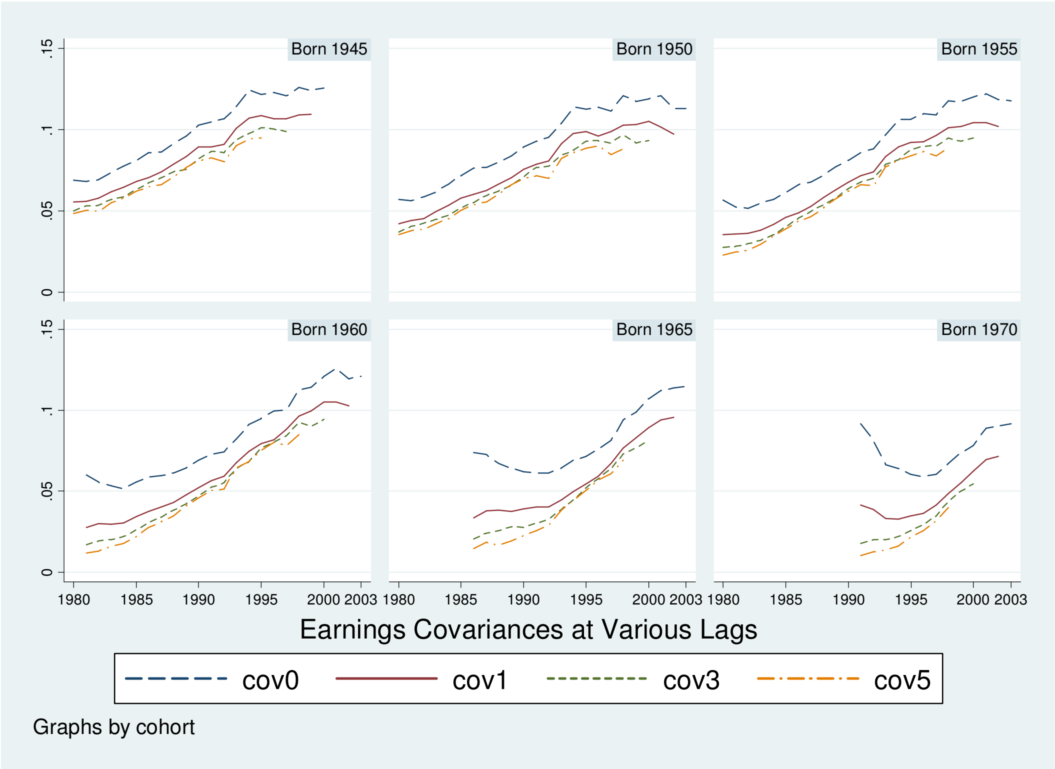

Figure 2: Predicted variance components