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Abstract

We investigate the relationship between life-cycle wages and flexicurity in Denmark. We separate permanent from transitory wages and characterise flexicurity using membership of unemployment insurance funds. We find that flexicurity is associated with lower wage growth heterogeneity over the life-cycle and greater wage instability, changing the nature of wage inequality from permanent to transitory. While we are in general unable to formally test for moral hazard against adverse selection into unemployment insurance membership, robustness checks suggest that moral hazard is the relevant interpretation.

JEL-Code: J310, J650.

Keywords: unemployment insurance, wage dynamics, wage inequality, wage instability.

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1. Introduction

The Danish "flexicurity" system has often been put forward 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 (UI) coupled with the absence of firing restrictions. Therefore, firms are free to manage labour demand, while an extended social safety net eliminates poverty risk and preserves social cohesion. Increasing labour market flexibility has been the goal of recent labour market reforms in Europe, for example 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 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. Flexicurity has been advocated in these Countries as a way of reducing income insecurity and welfare losses associated with labour market reforms.

In this paper we look at the relationship between individual wages and individual membership of UI funds which represents the security part of the Danish flexicurity system. There is an extensive literature documenting the disincentive effects that UI may exert on job search for 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 longer search, unemployment benefits may favour higher quality and longer lasting matches (Tatsiramos, 2009). While the wage effects of UI schemes are a less investigated topic, there are reasons to believe that they may also affect the productivity and wages of the employed, for example through moral hazard effects.

We are the first to provide evidence on the relationship between individual wages and UI. We consider Danish men employed in the private sector 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 wage shocks. We relate the two wage components to individual membership of UI funds. Using time variation in membership status at the individual level, we are able to relate membership to changes in the inter-temporal covariance structure of wages. Our models are grounded in the well established literature on permanent and transitory wage dynamics (Moffitt and Gottschalk 2008).

We model the impact of UI fund membership on two key aspects of the individual wage process, life-cycle wage growth and wage instability. We find that UI affects both, reducing the heterogeneity of wage growth and increasing wage instability. We interpret these results in a moral hazard framework in which the provision of insurance reduces the incentives to care about the good insured. In our context, UI reduces incentives to learn on-the-job and increases shirking, translating into more compressed life-cycle dynamics and more wage instability. Our results also have implications for wage inequality, whose nature changes from persistent to volatile when individuals join the UI scheme.

The maintained hypothesis for our interpretations is no selection into UI fund membership due to individual wage growth or wage instability. We cannot formally test moral hazard against selection, but we do perform a number of robustness checks whose results all support moral hazard effects rather than adverse selection.

The remainder of the paper is organised as follows. Section 2 discusses the policy background for flexicurity in Denmark and the relevant literature. Section 3 presents the models of wage dynamics used to investigate the impact of flexicurity. Section 4 describes the data and the estimation sample. Main results are presented in Section 5, while in Section 6 we subject them to robustness checks. Section 7 concludes.

2. Institutional background

Flexibility for employers to hire and fire workers and income security for the unemployed have both long been features of the Danish labour market. 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 until 2007. It is increasingly recognised that the *triplet* flexibility, income 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 in Denmark has been weak by international standards since the 1970's[1]. 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 and

[1] For a general description of the Danish labour market, see Andersen et al. (2005)

will usually depend on tenure in the job. 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.

Unemployment insurance is voluntary and organised into different funds along occupation and industry lines by labour unions.[2] They have common contribution rates and benefits and are heavily subsidised through general taxation. About 83% of the labour force belongs to a UI fund. Eligibility to benefits requires fund membership and employment for 12 months. In 2009 benefits were 90% of mean earnings over the previous three months subject to a maximum gross 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 most importantly is means tested, but would typically be 70% of unemployment benefit levels. The means testing implies for example that an owner-occupier could not receive benefits.

Effective conditionality for unemployment benefit receipt was introduced in 1994. Previously passive receipt of benefits for up to nine years could be extended indefinitely by enrolment in training programmes. Activation in the form of mandatory training and job search came in after 4 years of unemployment, where the unemployed is responsible for his own activation followed by 3 years where the UI system takes responsibility. Subsequently these time limits for the passive and active periods were reduced to 2+3 (1996), 1+3 (1998), 0+2 (2010). Activation for recipients of social assistance worked similarly in principle, but was not enforced until a recent reform which meant both groups were treated by the same authority.

Wage bargaining in the public sector has always been centralised and agreements are normally reached every second year. Since 2003 there has been a small element of

[2] Neumann et al, (1991) and Clasen and Viebrock (2008) describe organisation, membership and coverage of labour unions and unemployment insurance funds. Although there is an overlap between UI fund and trade union membership, there is not a one to one relationship between the two nor there exist any formal link. Union membership is at a lower rate compared with UI fund membership: 70 percent versus 83 percent.

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. Bargaining decentralisation became more and more widespread starting in 1993. There was a minimum amount of firm-level bargaining at around 4% until 1993, which increased to 21% by 2003.

In sum, flexicurity features most directly affect blue collar workers (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 UI fund membership

Our focus is on the relationship between UI fund membership and wage dynamics. Many economic models have been proposed to explain life-cycle wage and earnings growth. Rubinstein and Weiss (2006) in a recent survey group these into three broad classes: search, learning and investment. Search models emphasise the role of limited information and labour market frictions in determining wages. Workers look for jobs, job offers are made, workers decide whether to accept the offers and wages change accordingly (Burdett, 1978). Learning models focus on limited information regarding worker productivity. Workers are different, their productivity is only revealed to the employer gradually on-the-job and wages change accordingly (Gibbons and Waldman, 1999). Investment models emphasize human capital accumulation in school and at work. Workers invest in on-the-job training, trade off reduced current for higher future wages and wages evolve accordingly (Mincer, 1974).

Learning and search approaches emphasize within and between job wage growth respectively. Simple investment models ignore firm-specific human capital and on-the-job training is synonymous with general post-school investment. Many predictions are shared between models, but some predictions are distinctive to a particular class. Our aim is not to test the theories against each other. Rather, it is to estimate the simplest life-cycle wage model that will allow us to compare insured and uninsured workers in a theory-consistent way. By ignoring unemployment (assuming unobserved wages are missing at random) and employer identity (labour market experience is generic), we place our study in the earnings process econometrics literature, but rule out making inferences about job-specific wage evolution which would distinguish learning and search approaches. Indeed the only distinctive prediction we are able to test by assuming generic labour market experience comes from a simple model of investment in human capital. This merits describing in more detail as it will be the focus of interpretation of our model estimates.

This Mincer model of human capital investment can account for important features of life-cycle earnings.[3] After completing formal schooling and joining the labour force, workers forgo some potential earnings for the sake of investment in on-the-job training. This lowers earnings early in the work career and increases earnings later as returns to post-school investments accumulate. In the absence of investment in training, potential earnings equal observed earnings at labour market entry. With post-school investment, there is an "overtaking point" at which observed and potential earnings are equal. One can think of this as a break-even point at which the earnings of investors and non-investors coincide. It is also termed the Mincerian cross-over because it is the point at which differently shaped earnings profiles intersect.

Obviously one needs to carefully model individual life-cycle profiles in order to capture these phenomena, since observed earnings carry information about both long-term (or permanent) earnings and transitory fluctuations reflecting the unstable component of the earnings process. The distinction between two sources of income variation goes back at least to Friedman (1957) and empirically has been extensively investigated starting with the work of Lillard and Willis (1978). A number of studies have formalised permanent earnings over the life-cycle as an individual-specific age or experience profile, in which individual-specific intercepts measure human capital at labour market entry, whereas individual-specific slopes represent heterogeneity in productivity growth; a model that is typically referred to as a *random growth model*. Examples in the literature include Lillard and Weiss (1979), Hause (1980), Baker (1997), Haider (2001), Baker and Solon (2003), Cappellari (2004) and Gladden and Taber (2009). In this model, the Mincerian trade-off between initial earnings and earnings growth induced by training on-the-job translates into a negative covariance between individual-specific intercepts and slopes.

In this paper we are interested in the relationship between UI fund membership and life-cycle wage dynamics. We model wage dynamics distinguishing between long-term or permanent wages and transitory fluctuations, and specify the former as a *random growth* process consistent with a Mincerian model. In principle both the permanent and transitory wage components may depend on membership of a UI fund, for example because it may

[3] Surveys and extensions of the Mincerian earnings function approach are to be found in Heckman, Lochner, and Todd (2008) and Rubinstein and Weiss (2006).

affect incentives to learn or job retention. Therefore we extend standard models of permanent and transitory wages and allow UI fund membership to impact on the parameters governing both wage components. In what follows we start by specifying a standard model of wage dynamics which serves as a benchmark for our results; next we extend this baseline specification to account for the role of UI fund membership.

3.1 Baseline model

Our baseline specification is grounded in the extensive literature on the permanent/transitory decomposition of wages, (see Moffitt and, Gottschalk 2008, for a recent survey). We specify a model of individual wages and estimate the parameters of their inter-temporal covariance structure. Specifically, we postulate that

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

where w_{ict} is individual (i) log-wage deviation from the period (t) and cohort (c) specific mean, P and T superscripts denote permanent and transitory components, and the time span of observation is cohort specific. Permanent and transitory wages are orthogonal by definition, which allows their identification.

In line with the literature on *random growth models*, we specify long-term or permanent wages as an individual-specific linear profile in potential labour market experience EXP_{it}, defined as total time since first entering the labour market:

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

According to this specification, each individual's permanent wage is characterised by a starting wage (α_i) and a growth rate (β_i). The variances of individual-specific parameters ($\sigma^2{}_\alpha$ and $\sigma^2{}_\beta$) 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. As discussed above, a negative covariance indicates the existence of Mincerian a cross-over (Hause, 1980). Alternatively a positive covariance suggests that those with higher schooling learn faster on-the-job. Random growth represents the core of our permanent wage specification, and we allow it to flexibly vary over birth cohorts and calendar time through a set of loading factors π_t and λ_c.[4] Note that the time shifters can account for changes in the economic environment over time, including the sequence of labour market reforms discussed in the previous section, so that estimation of random growth parameters will not be biased by secular trends. Assuming independence between potential labour market experience and random growth parameters, the permanent wage auto-covariance implied by this model can be written as:

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

where EXP_i is the vector collecting individual observations of potential labour market experience.[5]

For the transitory wage model, in line with previous studies we adopt a low order ARMA process, in order to capture the fact that shocks to wages do not fade away instantaneously, but only after a few time periods. In particular, here we adopt an AR(1).[6] We also allow for flexible time and cohort specific shifters in the transitory wage. Finally, as discussed by MaCurdy (1982), we treat the process as non-stationary and explicitly model the variance of its initial condition. In sum:

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

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:

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

[4] Meghir and Pistaferri (2004) and Alvarez, Browning and Ejrnæs (2010) estimate models of wage changes. There are no time or cohort shifters in those models and their approach would be inappropriate for our purposes because age/experience parameters would be confounded with calendar time or cohort effects.

[5] As discussed in Gladden and Taber (2009) the assumption of independence between random growth parameters and labour market experience, which is ubiquitous in the literature, fails if actual experience (i.e. time actually spent working since entering the labour market) is used in place of potential experience due to endogenous intermittency of labour force participation.

[6] 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.

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 results from the sum of (3) and (5).

3.2 Model with UI fund membership

We now extend the baseline model to allow for individual membership of a UI fund in each wage component. As discussed in the previous section, membership is voluntary and individuals may change membership status, which generates time variation in membership at the individual level. Also, we know that typically labour market entrants are not insured, so that any impact of UI fund membership on entry wages would be both unlikely to occur and hard to interpret (see Ibsen and Westergård-Nielsen, 2008, and the data description in the next section). We therefore augment the random growth model by allowing for a change in individual wage growth associated with membership.[7] Let F_{it} be a dummy indicator for whether individual i is a UI fund member in year t. Our extended random growth model becomes:

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

The additional individual-specific parameter δ_i measures the change in the slope of the individual experience profile associated with membership of a UI fund. The second moments of δ_i provide information on the degree of heterogeneity in slope differentials (σ^2_δ) and their interrelationships with baseline intercepts and slopes ($\sigma_{\alpha\delta}$ and $\sigma_{\beta\delta}$). For example, the sign of $\sigma_{\beta\delta}$ indicates whether the wage growth of fast tracks (high β) accelerates (high δ, $\sigma_{\beta\delta}$ positive) or slows down (low δ, $\sigma_{\beta\delta}$ negative) with membership.

Assuming independence between the membership dummy F_{it} and the vector of individual specific parameters (α_i, β_i δ_i), the inter-temporal covariance structure for permanent wages becomes:

[7] In preliminary analyses we also used a model with differential entry wages for members, finding results entirely in line with those presented here.

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

where F_i is the vector collecting individual observations of UI fund membership.

Several points need to be made about identification of the additional parameters. First, identification requires individual level variation in UI fund membership over time periods and birth cohorts. This is something that is present in our data as we document in the data section. Second, we are not assuming independence of membership and potential experience, which would contradict the empirical observation that it takes some time in the labour market before individuals become members; rather, we exploit the correlation between the two variables for estimating the extra parameters. Third, while we cannot test the assumption of independence between individual specific parameters and the membership dummy, in Section 6 we provide robustness checks indicating that our results are not driven by selection into membership.

To characterise the link between wage instability and UI fund membership, we need to take a different approach to the one followed with the permanent wage, given that the instability parameter σ^2_ε is not individual-specific. We therefore parameterise the variance of white noise innovations with respect to the incidence of insurance coverage across cohorts and years, F_{ct}:[8]

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

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 and UI membership. Note that cohort and time trends in the transitory wage are already controlled for non-parametrically by the factor loadings τ and μ, so that ψ will not capture variation in instability over cohorts and time, but rather the effect of UI on instability in a difference-in-differences setup. Substituting σ^2_ε in (5) with $\sigma^2_{\varepsilon ct}$ yields the theoretical transitory wage auto-covariance function that we use in the analysis. Adding it to (7) provides the total

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

wage auto-covariance function that accounts for UI fund 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 wages implied by the specified model is mapped into empirical second moments of the within-cohort inter-temporal distribution of wages $A_c=N_c^{-1}\Sigma_{i\in c}A_i$, 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 of the estimation method are provided in the Appendix.

4. Data and descriptive statistics

We use administrative register data on gross hourly wages for the Danish labour force between 1980 and 2003. We consider men only, in common with the literature on wage components models, with the aim of excluding the more intermittent labour force participation of women which would otherwise inflate wage instability. Similarly, we focus on prime age men, aged 21-55, who are full-time private sector employees.

Given that we work on within cohort wage differentials, it is important to define sample selection also according to the year of birth. In order to have a sufficiently long period of observation we require that each cohort is observed for at least ten time periods. The youngest birth cohort in our sample is the one that turns 21 (and thus meets the selection criteria on age) in 1994 (and thus is observed at least ten times periods before the sample period ends), i.e. the birth cohort of 1973.. In principle, we could reason symmetrically at the other end of the sample period and use as the oldest group men that turn 55 in 1989 (thus being observed at least ten times after the beginning of the sample period), i.e. the birth cohort of 1934. However, the information needed to reconstruct potential labour market experience – in turn a crucial variable for the analysis — is censored for older cohorts, and the oldest cohort for which we have the information needed in the analysis is that of 1943. In sum, we use information on men born between

1943 and 1973, and we group them into 31 single-year birth cohorts. We allow individuals in these cohorts to enter and exit the panel according to the specified age criteria even if there are valid observations for them outside this 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 drop the lower and upper 0.5 percent of the resulting wage distribution of each year. Next we further exclude (the remaining few) wage observations falling below the minimum wage. Finally, for each individual, we require valid wage observations for at least five consecutive years to ease the identification of individual wage profiles.[9] 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 presented in Table 1. As a benchmark, we also provide statistics for the overall population of men aged 21-55 employed in the private sector. The estimating sample consists of roughly 810,000 individuals for a total of about 12.5 million person-year observations. Equivalent numbers in the comparison population of private sector prime-aged male employees are about 1.4 million an 17.0 million, with the larger churning in the latter group reflecting the fact that there we do not restrict to specific birth cohorts and do not impose restrictions about the minimum number of consecutive valid wage observations. There are differences concerning the average age. In particular, limiting the set of birth cohorts translates into faster growth of the age variable in the sample compared with the population. This is also reflected in the wage distribution. In both cases there is 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 16 percent if we look at the comparison population. Also, the standard deviation of the distribution almost doubles in the sample, while it grows by 37

[9] This latter sample selection rule is intermediate between the one used by Baker and Solon (2003), i.e. continuous earnings strings for each individual, and the approach of Haider (2001), who allows individuals to move in and out of the sample with the only requirement of having two positive but not necessarily consecutive valid observations on earnings. As a robustness check we also estimated the main model requiring only a minimum of two consecutive wage observations per worker. Our conclusions, discussed in the next section, were unaffected by the use of this alternative sample.

percent in the labour force. Finally, the table reports tabulation of unemployment insurance coverage. As can be seen this is rather high in both the estimating sample and the comparison population. However, in the former case it grows more substantially during the middle years of the panel and, again, the fact that there are no young cohorts entering the sample in these middle years explains 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 born between 1943 and 1947 reach the age of 55 before the end of the sample period and therefore stop contributing between 1999 and 2003. Intermediate cohorts (born between 1948 and 1959) belong to the 21-55 age range throughout the sample period. Finally cohorts born from 1960 onwards turn 21 after 1980, and therefore start contributing to estimation after the beginning of the sample period. 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. Those statistics are cross-sectional and uninformative about individual level variation in UI fund membership over time, which is crucial for the estimation of our model. Existing studies show that there is an age related element to UI fund membership, namely individuals join a few years after entry in the labour market, say in their late 20’s or early 30’s (see Ibsen and Westergaard-Nielsen, 2008). In order to provide more direct evidence on individual variation in UI fund membership, in Table 3 we exploit the longitudinal and birth cohort dimension of the data. The table reports entry and exit rates to and from UI fund membership by birth cohort, defined as the proportions becoming members or non-members from one year to the next. As can be seen, there is some “churning” between membership and non membership, with exit rates that are considerably lower than entries.

Importantly, transition rates are higher for younger cohorts, reflecting that on average the decision to join a UI fund is taken in the initial phases of the work career.

<FIGURE 1>

As a last piece of descriptive evidence, we present the covariance structure of time and cohort de-trended log-hourly wages, i.e. the empirical second moments of the inter-temporal wage distribution that are to be analysed by means of the model presented in Section 3. 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, which reflects the growth of wage dispersion obvious from Table 1. For each cohort, the series tends to shift downwards as we move from the variance to higher order auto-covariances. This reflects the presence of transitory wage shocks that show up in the variance but fade away the greater the time interval over which covariances are estimated. Finally, also note a downward shift in the covariance structure as we move to younger cohorts. This is consistent with heterogeneous growth rates in permanent wages.

5. Results

Before discussing the central results about flexicurity and life-cycle wage dynamics, it is instructive to look at overall model predictions in terms of variance decomposition over time. Figure 2 presents this 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 flexible shifters by cohort and time on each wage component. Considering the variance decomposition implied by the model reveals that permanent wage inequality seems to be the driver of increasing total variance most of time and for most cohorts. Wage instability, on the other hand, is generally constant, except 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. These patterns differ across cohorts: most evidently, younger cohorts have greater instability.

<TABLE 4>

5.1 *Baseline model.*

In Table 4 we report the core parameter estimates for the wage model of Section 3, while the full set of estimated time and birth cohort shifters on the two wage components are presented in Appendix Table A1.[10] 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 These estimates are presented in the first column of the table.

Parameters of the permanent component indicate the existence of substantial heterogeneity in both starting wages (σ^2_α) and wage growth rates (σ^2_β). The estimates imply that someone located one standard deviation above the mean in the distribution of wage growth rates sees his wage growing 2.8 percentage points faster than the mean (= $\sqrt{\sigma^2_\beta}$). The two sources of heterogeneity are negatively correlated ($\sigma_{\alpha\beta}$<0): individuals who enter the labour market with high wages also experience the slowest growth over the life-cycle, and vice-versa. The result is common to many studies in the literature: see Hause (1980), Baker (1997), Baker and Solon (2003), Gladden and Taber (2009). The leading interpretation for this finding is that it reflects the trade-off between initial earnings and earnings growth as predicted by the Mincer model. We should therefore expect a cross-over of wage profiles. Long-term inequality first decreases and then increases over the life-cycle, increases taking place after the cross-over. Hause (1980) computes the cross-over point t^* as the year in which permanent inequality is at its minimum: $t^*=-\sigma_{\alpha\beta}/\sigma^2_\beta$.[11] Our estimate of the cross-over from this baseline model is at 4.25 years of potential labour market experience (s.e.=0.15), approximately one year larger than the estimate obtained by Hause in a sample of Swedish men in the 1960s.

[10] Models with unrestricted loading factors produced negative and non significant estimates of the permanent wage loading factors for the two youngest cohorts. To overcome this issue, we constrained permanent wage loading factors to be the same on the five youngest cohorts . Core parameter estimates were very similar in the constrained and unconstrained models.

[11] Note that this is also the negative of the regression coefficient of intercepts on slopes.

Consider now the transitory wage of the baseline specification. All core parameters are precisely estimated. The autoregressive coefficient indicates the weight that lagged transitory shocks have on earnings volatility, the weight being given by the coefficient exponentiated using the lag. The estimate of ρ (=0.77) implies that the effects of transitory innovation is negligible after 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.

5.2 Model with UI fund membership

The second column of Table 4 presents estimated parameters for permanent and transitory wages in the model with UI fund membership. There is a substantial difference in wage growth between members and non-members of UI funds, the estimated variance of wage growth differentials σ^2_δ being statistically significant and of a size that is comparable with the baseline parameter σ^2_β. However, taken in isolation this coefficient is not informative on whether UI is associated with more or less growth rate heterogeneity. Making statements about the way wage profiles change when individuals are members of UI funds requires taking into account the estimated covariances between baseline parameters and slope shifters. The covariance between baseline slopes and slope shifters ($\sigma_{\beta\delta}$) is statistically significant and negative, indicating that UI fund membership is associated with compression of the distribution of wage growth rates, which would occur if fast tracks slow down on joining a UI fund. These estimates imply that someone located one standard deviation above the mean in the distribution of wage growth rates sees his wage growing 2.9 percent (=$\sqrt{\sigma^2_\beta + \sigma^2_\delta + 2\sigma_{\beta\delta}}$) faster than the mean if he is a member, which compares with 3.9 percent for non-members (=$\sqrt{\sigma^2_\beta}$). Consequently, as labour market experience accumulates, permanent inequality becomes greater among non-members than members. The other new parameter in the model with UI fund membership (i.e. the covariance between intercepts and the slope shifter $\sigma_{\alpha\delta}$) is positive (and significant), which is coherent with the other two negative covariances estimated for this model. These parameters combine to generate a cross-over point that is very similar for members and non-members at 3.9 and 4.2 years of labour market experience, respectively.[12]

<FIGURE 3>

Estimated patterns of permanent wage inequality over the life-cycle for members and non members are reported in Figure 3, which uses core random growth parameters (without the period and cohort factor loadings) to predict the variance of permanent wages. The random growth model implies that life-cycle inequality is quadratic in experience. At the start of the life-cycle the two profiles overlap by construction. During the initial phase of the working life, permanent inequality is low and almost indistinguishable between the two groups. Some differences start to emerge after ten years of experience, and they are apparent by twenty years. By the end of the working life the gap between the two groups is sizeable. Non-members have long-term inequality that is almost double that of members.

Consider now the transitory wage in the main model. Comparing these results with those from the baseline model shows that parameter estimates are rather stable. The one parameter whose estimate differs across models is the variance of AR(1) innovations (σ^2_ε), and the reason is that in the baseline case the parameter measures average (across levels of UI membership) instability, whereas in the second it measures instability for the (hypothetical) case of no UI membership. The additional parameter ψ measures the instability shift associated with UI fund membership. The positive estimate indicates that UI fund membership corresponds to more wage instability.

<FIGURE 4>

We use estimates of the random growth parameters, the AR(1) parameters and the factor loadings on time and cohorts to predict inequality in the two wage components for members and non-members of UI funds over the life-cycle. For each birth cohort we use parameter estimates to predict variance components, and then average predictions over

[12] Note that the computed cross-over point is a non linear function of estimated parameters so that the point computed in the baseline model does not need to belong to the interval defined by the equivalent points for members and non-members in the model with UI membership.

cohorts. Results are presented in Figure 4. The graph shows in Panel a) that UI fund membership is associated to lower permanent inequality throughout the life-cycle, with the gap between non-members and members widening with potential labour market experience. This reflects the large dispersion of wage growths rates found among non-members. Transitory inequality has the opposite pattern, see panel b) of the graph. There is a decline of earnings instability with experience for both members and non-members, reflecting the lower volatility of older cohorts. Differences between members and non-members are striking. For non members the decline is smooth and almost complete within the first ten years of labour market experience. For members, the life-cycle decline is slower (actually there is a slight increase over initial years) and there is no tendency for instability to disappear even for high levels of labour market experience. Overall, Figure 4 illustrates that membership of UI funds is associated with a shift in the nature of wage differentials, from permanent to transitory.

5.3 Discussion

These results show that while permanent inequality is lower for UI fund members because of more compressed returns to experience, their wage instability is larger than that of non members. Moral hazard effects can explain both results. Being insured may weaken the incentives to care about the good which is 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 progression. 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 work history more unstable and generate the greater wage instability that we observe. According to this interpretation, UI has a causal effect on the wage process, and changes the nature of wage inequality from permanent to transitory.

Clearly, the validity of moral hazard interpretations requires that the identification assumptions introduced in Section 3 hold. First we have assumed independence between UI fund membership and individual specific wage growth differentials, which enabled us to derive the moment restrictions for permanent wages in the model with UI fund membership, see equation (7). Second, we have assumed that differences in wage instability across cohorts and time periods are absorbed by the set of birth cohorts and calendar time shifters on transitory wages, so that we can use variation in the incidence of

UI fund membership across cohorts-period cells to estimate the association between flexicurity and instability, which is the parameter ψ in equation (8).

Adverse selection into UI membership may lead to violation of the identification assumptions. One can think of examples of selection when there is heterogeneity in either wage growth and employment (and thence wage) instability. For example, learning ability may be seen as a way to insure oneself against the risks of job loss. When workers reach the peak of learning capacity and their wage growth slows down, they may think of supplementing learning-based self insurance with fund-based insurance. Hence, it would not be the presence of UI that weakens wage growth, but rather the anticipation of a slowdown in wage progression that induces individuals to join the scheme. Similarly, individuals with intrinsically low job attachment (and therefore highly volatile wage profiles) may join the insurance scheme more than workers with higher employment stability. We assess the plausibility of adverse selection interpretations in the next section.

6. Sensitivity analyses

We begin our robustness checks by looking for evidence of selection into membership due to lagged wage growth and lagged wage volatility. In the presence of adverse selection effects we should observe a negative effect of lagged wage growth on UI fund membership --because individuals join a fund when wage growth slows down-- and a positive relationship between lagged wage instability and membership --because individuals join a fund when their wage profiles become more volatile. We define wage growth as the log wage change between two consecutive years, and we estimate models in which individual membership indicators are regressed on lagged wage growth. We proxy wage instability (which is a variance and thus is not defined at the individual level) using individual specific measures of wage volatility. For this exercise, we take an approach similar to Gottschalk and Moffitt (1994) and derive transitory wages as the log-wage deviation from individual specific multi-year averages. In our case, we average wages over 5-year rolling windows and consider only cases that belong to the balanced panel of each window. Wage volatility is defined as the sum of either squared or absolute deviations from the average.[13] We regress UI membership indicators upon the lags of these volatility measures.

[13] Ziliak et al (2011) use series of bi-annual panels from the U.S. Currerrent Population Survey and define earnings volatility as a function of squared year-to-year percentage wage changes.

<TABLE 5>

Results are reported in Table 5. All models include controls for industry and local unemployment (i.e. the main determinants of UI fund membership) plus time and age trends. The outcome variable in these regression is the individual sequence of UI fund membership status, limiting the sample to cases in which individuals join the UI scheme. In particular we focus on sequences in which there is non-membership for 3 years followed by membership in the fourth year, after which we stop following the individual, and sequences in which non-membership for 3 years is followed by membership until the end of the observation window. Analysis of the first type of sequence conveys information about joining the UI scheme, whereas we use the second type of sequence to look at stable entries into the scheme. Given the particular type of sample selection rules applied, we used fixed effects regressions throughout in order to avoid issues of spurious correlation induced by (time invariant) unobserved heterogeneity. We analyse the membership sequences by logit and linear probability models.

The first row of Table 5 reports results for lagged wage growth.[14] The sign of the estimated coefficients is always positive, whereas they are statistically significant only in the right part of the table in which stable entries into UI is analysed. More importantly for our purposes, none of the estimated effects is negative, as would be the case in the presence of selection effects

In the lower rows of the table we look at the relationship between UI entries and lagged wage volatility. In each of the cases considered the regression coefficient is negative and statistically significant, pointing towards a negative association between lagged volatility and the decision to join a UI fund. This is the opposite to what one would expect if selection on wage instability was driving the membership decision. Taken together with the results on wage growth, these findings support our identifying assumptions.

<TABLE 6>

[14] The table only reports coefficients of interest. Full sets of estimates are available upon request.

Our second robustness check is based on adjusting individual earnings for the effects of the main determinants of UI fund membership, namely industrial affiliation and the local unemployment rate. The aim of this exercise is to remove, in a reduced form fashion, the effects of observed heterogeneity in membership determinants from raw wages before estimating wage second moments. If unobserved heterogeneity in UI fund membership is driving our results and if this heterogeneity is correlated with observed UI determinants, then estimates from the model with UI fund membership should be sensitive to the adjustment for UI determinants.

Results from this exercise are presented in the first column of Table 6. Comparing these with their counterparts in Table 4, it is evident that findings are robust to the adjustment of raw earnings for the determinants of UI fund membership. Some of the estimated parameters, namely the variances of time-invariant components of permanent wages, are now smaller, which is a consequence of having removed sources of heterogeneity from the data. However, the general pattern of estimates confirms the evidence in Table 4, the main differences being larger variance of wage growth and lower autoregressive coefficients. Overall, results suggest that heterogeneity in the determinants of UI fund membership is not driving our main findings.

Our final robustness check concentrates on the second of our results, i.e. the positive effect of UI membership on instability. We allow the effect to differ across groups of workers which are known to be characterised by different degrees of wage or employment instability. If the result from Section 5.2 was driven by the selection of more unstable workers into UI membership, then we expect to find it only within more unstable groups. 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, because wages are more variable in this industry as there are more performance-based contracts. As for occupation, we consider the manual/non-manual partition, with the former group being the more unstable and having more varying wage contracts.[15] In each of the two cases, we interact

[15] Due to data limitations, we could estimate this particular model only for the 1980-1995 period. To solve some convergence issues arising over this shorter time interval, we calibrated $\sigma_{\alpha\delta}$ using its estimate from Table 4.

the binary partition with UI membership, 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 of this exercise are collected in the second and third columns of Table 6. In each case we find that the positive relationship between UI fund membership and wage instability is not dependent on the specific group of workers considered. Even for the more stable groups of workers (non-metal manufacturing and non-manual workers) there is a positive effect of UI fund membership on instability.

All of the robustness checks in this section support the view that selection into UI funds does not drive our headline results. This favours a moral hazard interpretation discussed in the previous section.

7. Concluding remarks

We have considered the relationship between individual wage trajectories over the life-cycle and membership of unemployment insurance funds in Denmark – the security part of flexicurity. We have used the population of prime-aged male private sector employee wages for 24 years to decompose the wage process into its permanent and transitory components and we have characterised the impact of insurance fund membership on each component.

We find that membership is associated with a reduction in wage growth rate heterogeneity that compresses the long-term or permanent wage distribution. On the other hand, there is greater wage instability among UI fund members. We interpret these two findings as the symptoms of moral hazard effects associated with UI fund membership. More homogeneous life-cycle profiles associated with UI fund membership are consistent with lower incentives to accumulate skills on-the-job. Alternatively, the greater earnings instability associated with UI fund membership may results from greater employment instability. In principle our results could also stem from worker selection into membership of UI funds. We therefore subject the main findings to several robustness checks, all of which favour a moral hazard interpretation.

These results add to the literature on the effect of unemployment benefit by showing that UI may exert some effect also on employed individuals. Unemployment insurance exists to smooth consumption between periods of work by reducing transitory income fluctuations. We find UI fund members to have less permanent and more transitory wage dispersion than non-members. This greater transitory income variation in-work partially offsets reduced income variation when unemployed for the insured.

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 $S_c=K_c-t_{0c}$ 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 θ 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 $\mathrm{Var}(\theta)=(G'G)^{-1}G'VG(G'G)^{-1}$, where G is the gradient matrix evaluated at the solution of the minimisation problem.

Appendix Table 1: Estimates of shifters for time periods and birth cohorts (continues on next page)

	Main model				*Main model on industry-unemployment adjusted earnings moments*				*Model with industry-based instability/insurance effects*				*Model with occupation-based instability/insurance effects*			
	Permanent		*Transitory*		*Permanent*		*Transitory*		*Permanent*		*Transitory*		*Permanent*		*Transitory*	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Time shifters (1980=1)																
1981	0.9523	0.0032	0.9235	0.0033	0.9347	0.0038	0.9374	0.0034	0.9524	0.0032	0.9348	0.0035	0.9350	0.0028	1.0838	0.0062
1982	0.8801	0.0038	0.8884	0.0039	0.8709	0.0044	0.9173	0.0040	0.8804	0.0038	0.9094	0.0046	0.8626	0.0038	1.1548	0.0079
1983	0.8687	0.0041	0.8585	0.0041	0.8736	0.0049	0.8813	0.0042	0.8694	0.0041	0.8836	0.0051	0.8518	0.0042	1.1464	0.0084
1984	0.8660	0.0044	0.8243	0.0041	0.8839	0.0052	0.8453	0.0042	0.8666	0.0044	0.8478	0.0050	0.8521	0.0046	1.1004	0.0083
1985	0.8585	0.0045	0.8214	0.0042	0.8838	0.0054	0.8405	0.0042	0.8590	0.0045	0.8424	0.0048	0.8485	0.0047	1.0982	0.0084
1986	0.8505	0.0047	0.8092	0.0041	0.8886	0.0057	0.8294	0.0041	0.8509	0.0047	0.8309	0.0049	0.8345	0.0050	1.1057	0.0087
1987	0.7864	0.0054	0.7833	0.0042	0.8173	0.0064	0.8234	0.0043	0.7869	0.0054	0.8073	0.0050	0.7786	0.0064	1.1215	0.0088
1988	0.7739	0.0054	0.7478	0.0042	0.8060	0.0065	0.7868	0.0042	0.7739	0.0054	0.7705	0.0049	0.7631	0.0064	1.0989	0.0089
1989	0.7575	0.0055	0.7193	0.0042	0.7903	0.0065	0.7570	0.0042	0.7564	0.0055	0.7385	0.0047	0.7459	0.0065	1.0838	0.0090
1990	0.7628	0.0056	0.6928	0.0041	0.8015	0.0067	0.7337	0.0042	0.7607	0.0056	0.7105	0.0046	0.7428	0.0065	1.0755	0.0091
1991	0.7315	0.0055	0.6901	0.0042	0.7667	0.0066	0.7286	0.0043	0.7295	0.0055	0.7086	0.0047	0.7146	0.0065	1.0906	0.0095
1992	0.6921	0.0061	0.6820	0.0042	0.7354	0.0073	0.7202	0.0043	0.6918	0.0061	0.7033	0.0049	0.7022	0.0076	1.0562	0.0095
1993	0.7240	0.0064	0.6159	0.0039	0.7691	0.0077	0.6507	0.0040	0.7240	0.0064	0.6379	0.0047	0.7038	0.0077	1.0056	0.0089
1994	0.7321	0.0065	0.6185	0.0038	0.7903	0.0079	0.6527	0.0039	0.7324	0.0065	0.6427	0.0047	0.7017	0.0078	1.0106	0.0090
1995	0.7094	0.0063	0.5680	0.0043	0.7715	0.0077	0.6040	0.0044	0.7106	0.0063	0.5872	0.0049	0.6600	0.0074	1.0674	0.0112
1996	0.6818	0.0053	0.5588	0.0045	0.7273	0.0064	0.5983	0.0046	0.6823	0.0053	0.5808	0.0052				
1997	0.6375	0.0050	0.5819	0.0048	0.6830	0.0060	0.6214	0.0049	0.6377	0.0050	0.6091	0.0059				
1998	0.6311	0.0049	0.6350	0.0052	0.6696	0.0059	0.6743	0.0053	0.6306	0.0049	0.6687	0.0067				
1999	0.5949	0.0046	0.6688	0.0055	0.6272	0.0055	0.7110	0.0055	0.5938	0.0046	0.7098	0.0075				
2000	0.5728	0.0045	0.7001	0.0057	0.6029	0.0053	0.7412	0.0057	0.5712	0.0044	0.7469	0.0081				
2001	0.5463	0.0043	0.7287	0.0060	0.5717	0.0050	0.7707	0.0059	0.5444	0.0043	0.7796	0.0087				
2002	0.5065	0.0040	0.7315	0.0060	0.5287	0.0047	0.7738	0.0060	0.5049	0.0040	0.7895	0.0094				
2003	0.4859	0.0039	0.7409	0.0061	0.5094	0.0045	0.7805	0.0061	0.4843	0.0038	0.8068	0.0103				

Cohort shifters (1958=1)																
1943	0.6104	0.0061	0.8544	0.0089	0.6164	0.0066	0.8536	0.0087	0.6093	0.0060	0.8562	0.0089	0.5975	0.0059	0.8964	0.0094
1944	0.6281	0.0061	0.8620	0.0084	0.6314	0.0066	0.8676	0.0082	0.6273	0.0061	0.8699	0.0085	0.6162	0.0060	0.8957	0.0090
1945	0.6399	0.0061	0.8653	0.0079	0.6469	0.0066	0.8673	0.0078	0.6393	0.0061	0.8678	0.0081	0.6258	0.0060	0.9088	0.0087
1946	0.6539	0.0061	0.8801	0.0074	0.6528	0.0066	0.8912	0.0072	0.6536	0.0061	0.8870	0.0076	0.6471	0.0061	0.9090	0.0085
1947	0.6796	0.0064	0.9082	0.0072	0.6805	0.0069	0.9126	0.0071	0.6793	0.0064	0.9165	0.0074	0.6769	0.0064	0.9321	0.0085
1948	0.7127	0.0068	0.9113	0.0072	0.7103	0.0073	0.9211	0.0070	0.7127	0.0068	0.9276	0.0077	0.7118	0.0068	0.9369	0.0083
1949	0.7285	0.0072	0.9191	0.0072	0.7269	0.0077	0.9304	0.0070	0.7284	0.0072	0.9257	0.0073	0.7373	0.0072	0.9342	0.0079
1950	0.7505	0.0073	0.9086	0.0070	0.7509	0.0079	0.9165	0.0069	0.7503	0.0073	0.9234	0.0073	0.7598	0.0074	0.9273	0.0077
1951	0.7936	0.0077	0.9199	0.0070	0.7919	0.0084	0.9252	0.0069	0.7943	0.0077	0.9419	0.0078	0.8060	0.0079	0.9446	0.0079
1952	0.8232	0.0080	0.9160	0.0069	0.8183	0.0085	0.9255	0.0067	0.8234	0.0080	0.9253	0.0071	0.8413	0.0083	0.9308	0.0076
1953	0.8408	0.0081	0.9298	0.0067	0.8361	0.0087	0.9360	0.0066	0.8411	0.0081	0.9419	0.0069	0.8640	0.0084	0.9420	0.0073
1954	0.8620	0.0083	0.9400	0.0067	0.8568	0.0089	0.9464	0.0066	0.8621	0.0083	0.9537	0.0070	0.8804	0.0086	0.9612	0.0073
1955	0.9054	0.0086	0.9501	0.0067	0.9056	0.0093	0.9582	0.0065	0.9075	0.0086	0.9558	0.0069	0.9230	0.0089	0.9619	0.0074
1956	0.9394	0.0089	0.9606	0.0066	0.9438	0.0097	0.9661	0.0065	0.9409	0.0089	0.9686	0.0069	0.9439	0.0092	0.9812	0.0073
1957	0.9758	0.0092	0.9739	0.0064	0.9759	0.0099	0.9783	0.0063	0.9766	0.0092	0.9722	0.0065	0.9772	0.0094	0.9916	0.0072
1959	1.0246	0.0097	1.0029	0.0064	1.0309	0.0104	1.0014	0.0063	1.0250	0.0097	1.0006	0.0064	0.9920	0.0097	1.0164	0.0072
1960	1.0334	0.0097	1.0787	0.0073	1.0357	0.0105	1.0602	0.0070	1.0323	0.0097	1.0647	0.0074	0.9877	0.0097	0.9031	0.0082
1961	1.0495	0.0099	1.0865	0.0074	1.0548	0.0107	1.0666	0.0071	1.0502	0.0099	1.0743	0.0074	0.9778	0.0097	0.9144	0.0081
1962	1.0698	0.0102	1.1293	0.0077	1.0741	0.0110	1.1105	0.0075	1.0696	0.0102	1.1134	0.0078	0.9830	0.0101	0.9443	0.0083
1963	1.0880	0.0105	1.1601	0.0079	1.0984	0.0114	1.1339	0.0077	1.0873	0.0105	1.1441	0.0080	0.9569	0.0101	0.9807	0.0086
1964	1.1241	0.0111	1.1948	0.0081	1.1284	0.0120	1.1681	0.0080	1.1213	0.0111	1.1757	0.0083	0.9672	0.0108	0.9980	0.0088
1965	1.1342	0.0117	1.2415	0.0086	1.1501	0.0128	1.1998	0.0083	1.1316	0.0117	1.2205	0.0088	0.9596	0.0117	1.0299	0.0092
1966	1.0982	0.0119	1.2875	0.0089	1.1085	0.0130	1.2438	0.0086	1.0953	0.0119	1.2694	0.0091	0.8942	0.0123	1.0677	0.0096
1967	1.0246	0.0124	1.3367	0.0094	1.0244	0.0136	1.2903	0.0090	1.0206	0.0124	1.3165	0.0096	0.8369	0.0137	1.1000	0.0102
1968	0.8855	0.0135	1.3855	0.0098	0.8729	0.0148	1.3441	0.0095	0.8810	0.0135	1.3726	0.0099	0.7294	0.0152	1.1505	0.0111
1969			1.4866	0.0107			1.4282	0.0101			1.4614	0.0109			1.2488	0.0122
1970			1.4588	0.0111			1.4044	0.0105			1.4501	0.0112			1.2643	0.0132
1971	0.6155	0.0112	1.4695	0.0114	0.6173	0.0120	1.4097	0.0108	0.6117	0.0112	1.4528	0.0115	0.5134	0.0147	1.2810	0.0140
1972			1.5354	0.0115			1.4697	0.0109			1.4860	0.0126			1.3275	0.0150
1973			1.5653	0.0130			1.4926	0.0121			1.5189	0.0138			1.4064	0.0178

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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	
	Sample (N=811651)	Comparison population (N=1370600)	Sample	Comparison population	Sample	Comparison population	Sample	Comparison population	Sample	Comparison population
1980	315546	617993	155.75	161.88	46.05	54.76	29.28	35.83	0.80	0.79
1981	326064	593473	155.63	161.43	44.48	52.52	29.87	36.00	0.81	0.80
1982	350632	600548	156.25	161.57	45.17	52.42	30.34	36.02	0.84	0.83
1983	376333	607457	157.75	162.39	47.00	53.72	30.81	36.02	0.84	0.83
1984	415394	641090	157.38	161.12	48.15	54.10	31.22	35.93	0.85	0.84
1985	450544	679105	162.30	164.82	50.39	55.53	31.56	35.85	0.84	0.84
1986	473543	691902	166.64	168.19	52.93	57.45	31.98	35.88	0.85	0.84
1987	483039	677038	176.58	178.04	55.89	60.55	32.43	35.95	0.89	0.88
1988	490382	661274	180.40	181.86	58.80	63.21	32.93	36.12	0.89	0.88
1989	509895	666010	181.28	182.45	60.49	64.53	33.42	36.25	0.90	0.89
1990	524817	666719	188.35	189.61	64.63	68.82	34.07	36.57	0.90	0.89
1991	540737	678325	191.50	191.74	66.45	70.02	34.62	36.79	0.90	0.89
1992	551213	672796	190.16	190.14	65.77	69.11	35.15	36.93	0.93	0.92
1993	558019	663030	182.33	181.99	65.91	68.66	35.69	37.10	0.94	0.93
1994	592607	691533	185.51	184.83	70.87	73.52	36.10	37.06	0.94	0.93
1995	606268	710180	189.13	186.70	71.06	73.01	36.81	37.11	0.95	0.93
1996	625657	739065	190.65	186.64	71.78	72.94	37.62	37.27	0.90	0.88
1997	635777	757390	189.67	184.28	71.02	71.41	38.45	37.39	0.90	0.87
1998	643997	770231	198.18	190.94	77.05	76.47	39.31	37.52	0.90	0.86
1999	639439	780972	198.63	190.83	77.82	76.74	39.79	37.74	0.89	0.85
2000	617047	788308	202.00	192.65	80.81	78.77	40.40	37.81	0.89	0.84
2001	585760	779092	206.95	196.44	84.16	81.14	40.96	37.96	0.89	0.84
2002	593564	954674	204.99	192.86	81.78	76.39	41.73	38.67	0.89	0.82
2003	563419	935796	200.28	188.20	80.11	74.49	42.24	38.80	0.89	0.81
All years	12469693	17024001	184.94	181.49	69.20	69.14	35.95	36.96	0.89	0.86

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: UI membership dynamics by birth cohort

Cohort	Entry rate	Exit rate
1943	10.88	0.40
1944	10.77	0.40
1945	10.71	0.43
1946	10.81	0.44
1947	10.55	0.47
1948	10.22	0.51
1949	10.50	0.55
1950	10.51	0.56
1951	10.52	0.57
1952	10.19	0.63
1953	10.91	0.65
1954	10.75	0.66
1955	11.45	0.69
1956	11.41	0.74
1957	12.30	0.79
1958	12.46	0.81
1959	12.56	0.83
1960	13.55	0.83
1961	11.97	0.81
1962	12.16	0.8
1963	12.51	0.82
1964	12.96	0.80
1965	13.99	0.85
1966	13.97	0.92
1967	16.06	0.96
1968	15.31	1.00
1969	15.50	1.14
1970	15.42	1.21
1971	15.53	1.38
1972	14.83	1.53
1973	15.49	1.69
All cohorts	12.23	0.74

Table 4: Baseline model and model with UI membership: Core parameter estimates

	Baseline Model		*Model with unemployment insurance*	
	Coeff.	S.E.	Coeff.	S.E.
Permanent wage				
σ^2_α	0.0079	0.00073	0.0130	0.00069
σ^2_β	0.0008	0.00002	0.0015	0.00005
$\sigma_{\alpha\beta}$	-0.0034	0.00010	-0.0066	0.00023
σ^2_δ			0.0015	0.00004
$\sigma_{\alpha\delta}$			0.0032	0.00024
$\sigma_{\beta\delta}$			-0.0011	0.00003
Transitory wage				
σ^2_0	0.0628	0.00059	0.0578	0.00064
σ^2_ε	0.0335	0.00041	0.0012	0.00011
ψ			3.8039	0.10568
ρ	0.7737	0.00089	0.7279	0.00122
SSR	0.1103		0.0992	

Note: the model includes flexible shifters for time periods and birth cohorts on each wage component, estimates are reported in Table A1. The model is estimated on 12469693 wage observations, corresponding to 811651 individuals observed between 1980 and 2003, and 6895 second moments of the within cohort intertemporal wage distribution.

Table 5: Insurance membership as a function of lagged wage growth and lagged wage volatility

	Joining				*Joining and staying*			
	FE-Logit		FE-OLS		FE-Logit		FE-OLS	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Lagged wage growth	0.0289	0.0226	0.0008	0.0018	0.1450	0.0279	0.0275	0.0042
Lagged volatility (squared)	-0.0539	0.0067	-0.0075	0.0009	-0.0225	0.0042	-0.0021	0.0003
Lagged volatility (absolute)	-0.0011	0.0001	-0.0002	0.0000	-0.0004	0.0001	-0.00003	0.00000

Note: each estimate comes from a different model. Regressions include controls for industry, local unemployment rates, age and time trends. Wage volatility is defined as the squared or absolute deviation of wages from the individual mean wage computed over a rolling window spanning the five years prior to observation, summed over the five years

Table 6: Sensitivity analysis on variance components models

	Main model on industry-unemployment adjusted wages		*Model with industry effects in the transitory component*		*Model with occupation effects in the transitory component (1980-1995)*	
	Coeff.	S.E.	Coeff.	S.E.	Coeff.	S.E.
Permanent wage						
σ^2_α	0.0172	0.00067	0.0142	0.00070	0.0527	0.00119
σ^2_β	0.0015	0.00004	0.0016	0.00005	0.0021	0.00005
$\sigma_{\alpha\beta}$	-0.0056	0.00020	-0.0065	0.00023	-0.0091	0.00014
σ^2_δ	0.0015	0.00004	0.0016	0.00004	0.0020	0.00005
$\sigma_{\alpha\delta}$	0.0024	0.00020	0.0030	0.00024	0.0032	
$\sigma_{\beta\delta}$	-0.0011	0.00003	-0.0011	0.00003	-0.0015	0.00003
Transitory wage						
σ^2_0	0.0552	0.00060	0.0558	0.00065	0.0371	0.00050
σ^2_ε	0.0016	0.00014	0.0010	0.00009	0.0032	0.00034
ψ	3.4258	0.09971				
ψ_1			14.4083	1.32379	2.4625	0.14256
ψ_2			3.3866	0.11815	1.4313	0.10979
ρ	0.7017	0.00119	0.7234	0.00128	0.5161	0.00170
SSR	0.0885		0.0989		0.0264	

Note: the model includes flexible shifters for time periods and birth cohorts on each wage component, estimates are reported in Table A1. The model is estimated on 12469693 wage observations, corresponding to 811651 individuals observed between 1980 and 2003, and 6895 second moments of the within cohort intertemporal wage distribution (numbers are equal to 7565033, 771899 and 2991 for the model with occupation specific instability).

Figure 1: Wages covariances at various lags

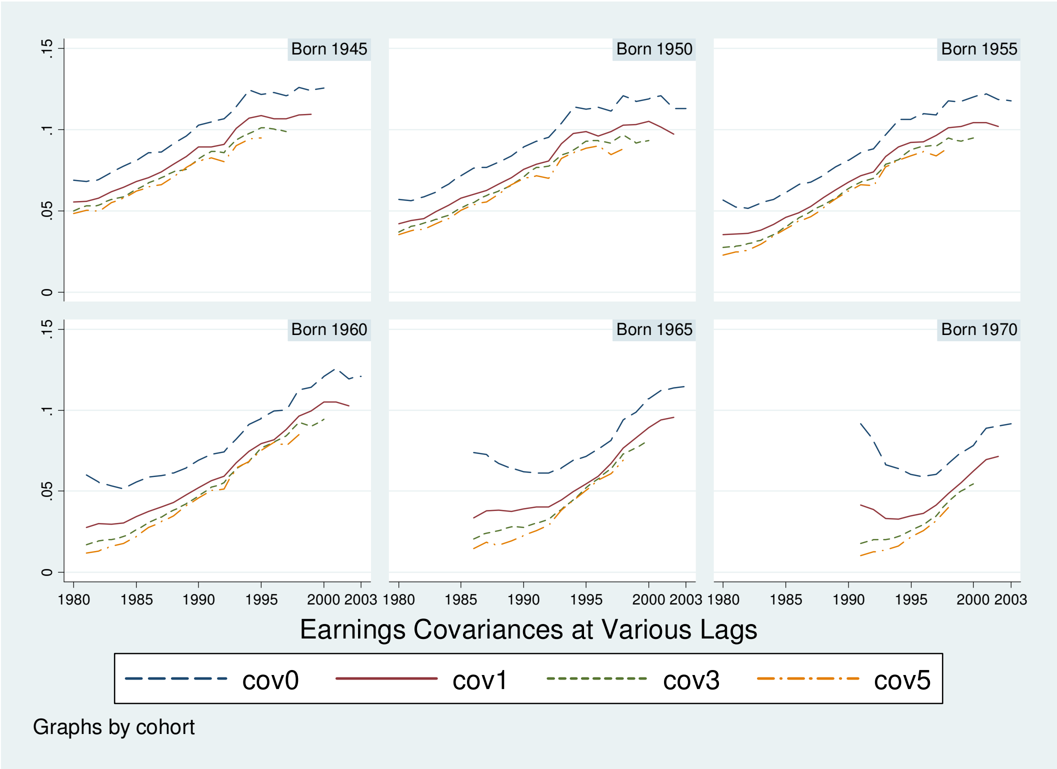


Figure 2: Predicted variance components

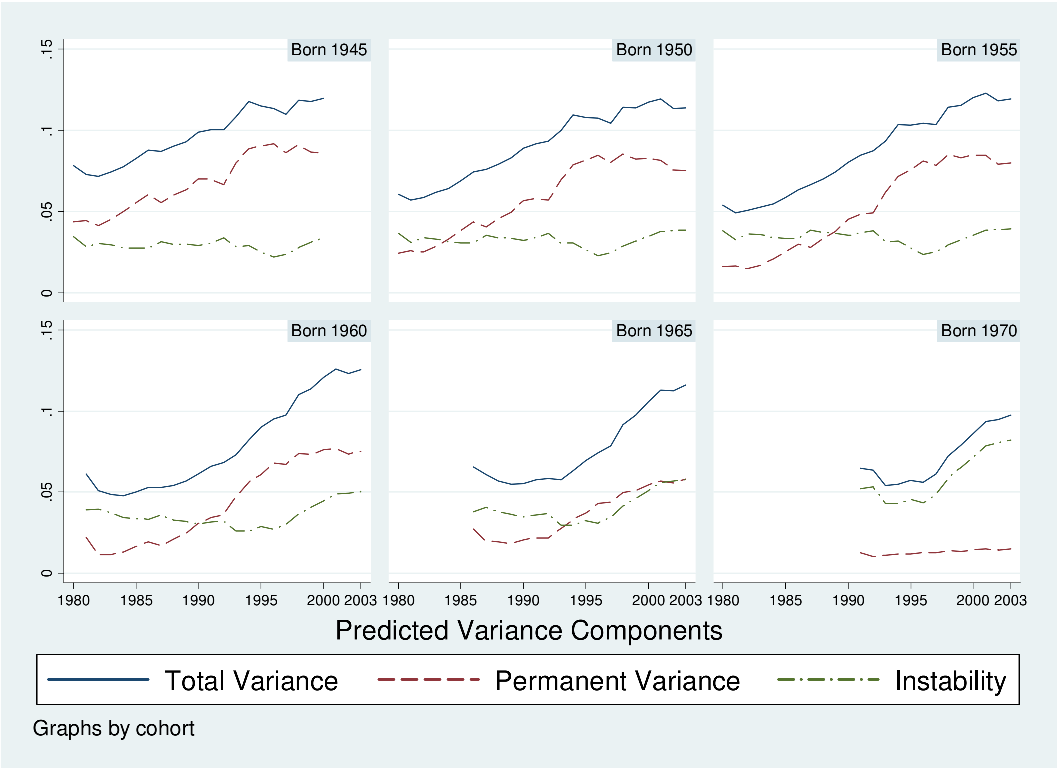


Figure 3: Permanent wage dispersion over the life-cycle by UI membership, net of cohort and time effects

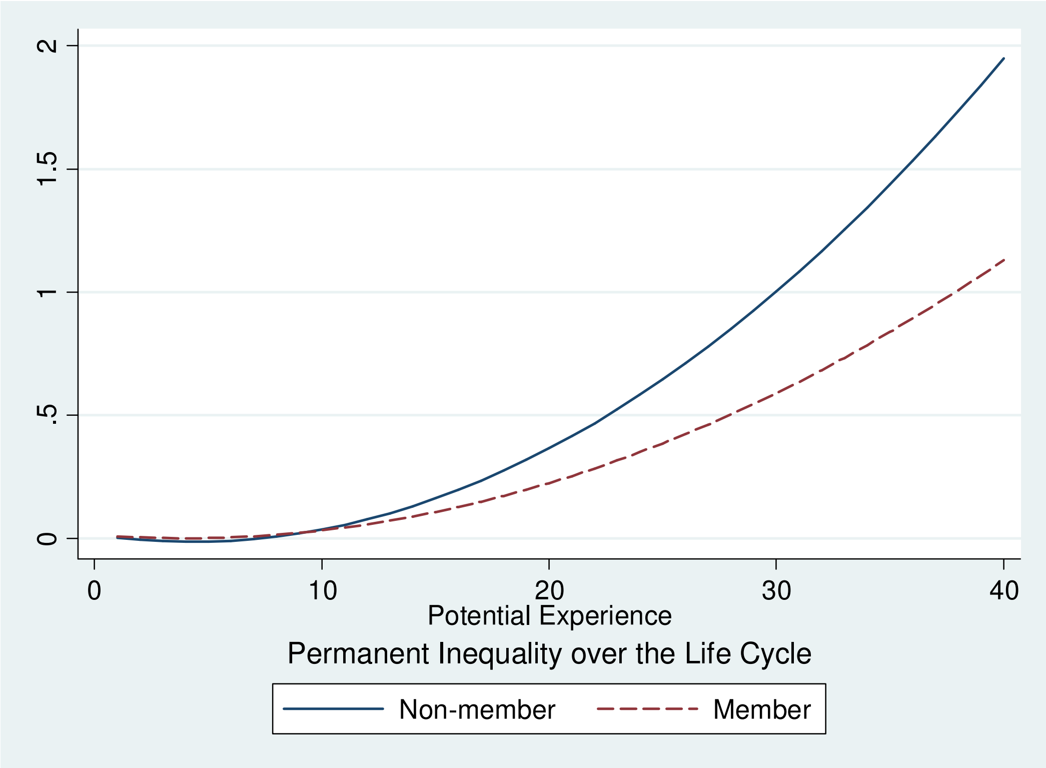
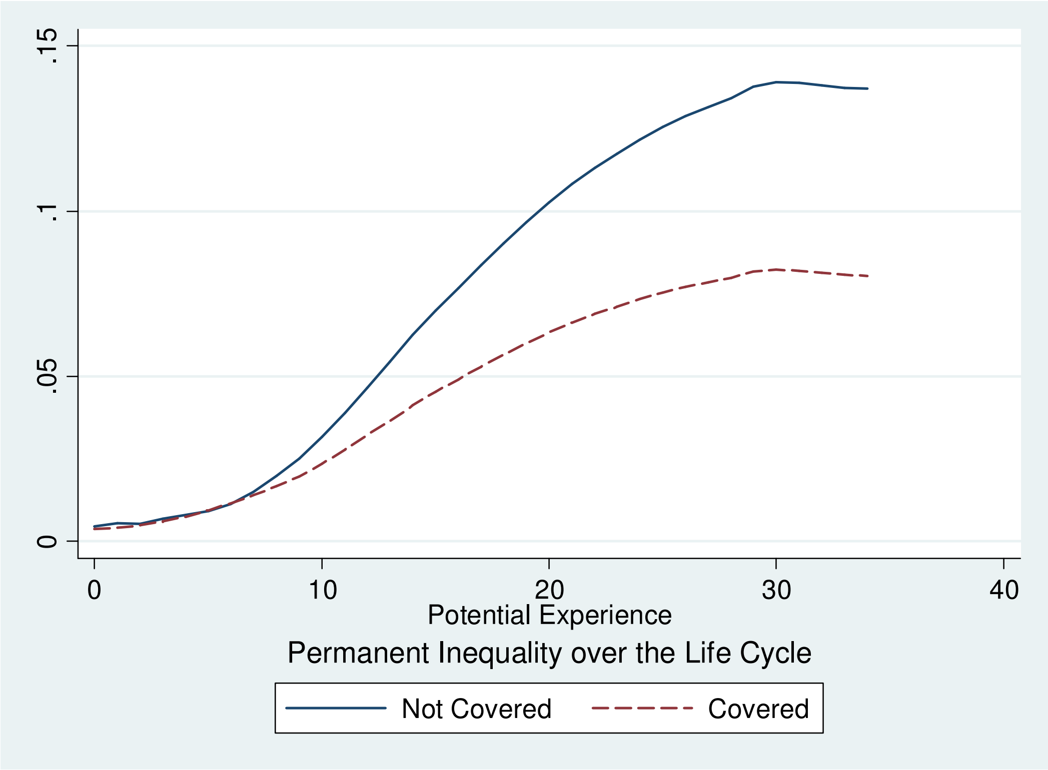


Figure 4: Components of wage dispersion over the life-cycle by UI membership

a) Permanent dispersion



b) Transitory dispersion