Job hazard pay and worker risk attitudes^{*}

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Abstract

We provide a fresh analysis of the theory of compensating wage differentials (CWD) using unusually rich and detailed data on self-reported work environment conditions and worker risk attitudes, from a representative 4-wave (1990-2005, 5-year spaced) panel survey of workers, which we link to the Danish register, longitudinal, yearly, matched employer-employee data. Our study improves and extends previous CWD empirical analysis in several ways: a). in standard hedonic wage equations, we control for both individual and firm-specific time-invariant unobserved heterogeneity; we also report spell first-difference estimates where workers report changes in work conditions, within the same job spell; b). we account for worker heterogeneity in attitudes towards health and safery risks, from information on workers' smoking habits, and on their being parents of young children; c) we compare the results in a) and b) above with alternative results obtained by estimating the workers marginal willingness to pay for job amenities from their job separation hazards. For a), we find that the only work environment conditions compensated for by hourly wage premia, in the order of 4-6%, are related to flexibility in the working time ("shift premia"), namely "working in irregular shifts", "working in the evening" and "working at night". If in addition we account for the selection of workers in hazardous jobs based on the observed worker risk proxies and time-invariant worker unobservables, cf. b), we find negative selection of risk-lovers into shift-jobs, with sizable hourly wage premia of 18-26%, while positive or no selection, and no compensation, in other types of hazard work. Finally, cf. c), shift-jobs CWD estimates based on the worker's employment history have magnitudes in between those at a) and b). We rationalize our empirical results via a parsimonious model of job hazard premia and worker risk profiles.

Keywords: compensating wage differentials, marginal willingness to pay, working conditions, hedonic wages, risk profiles, linked employer-employee data

JEL codes: J28, J31, J81

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1 Introduction

Research on job quality and workplace conditions has lately drawn renewed attention within the labour economics and industrial relations fields. The growing interest for job satisfaction data among labour economists has, for instance, generated a debate about the main factors explaining the worker's rating of her work environment (Clark, 2005). Many descriptive studies point out a trend of declining job satisfaction despite rising real wages, observed for example in European surveys. It is uncontroversial that nonpecuniary work conditions are considered crucial job aspects by individuals searching for jobs. To give one example, in seven OECD countries over the 1990s, as shown by Clark (2005) and reported also here in Table 1, employees overall do not rate income or hours as most important job features, the two aspects with highest ratings being job security and job interest, followed by work independence. These preferences appear consistent across the two genders. Job quality has also moved on fast to become an important economic policy issue, for instance through the definition of "decent work" by the ILO (ILO, 1999), or through the inclusion of "employment quality" indicators in the European Employment Strategy (European Commission, 2001). These definitions tackle a wide series of job dimensions, like minimum wage level, job security, representation rights, job safety, training opportunities, all of which can be enacted/affected by recommended labour and social policies etc.

Notwithstanding (scant) descriptive findings and general policy enthusiasm concerned with implementing "better" work conditions, backing up existing economic theory with hardcore empirical evidence is still in infancy. The formal version of the hedonic wage theory starts off with Rosen's (1974) widely cited study. In a Walrasian labour market, under perfect information about job characteristics, a compensating wage differential ought to be observed between workers facing job amenities relative to similar workers facing disamenities, at similar workplaces. In order to attract labor, an employer offering hazardous or otherwise undesirable jobs must pay higher wages than employers offering jobs with more desired nonwage aspects. Therefore any individual faces a set of jobs with different combinations of wage and nonwage attributes. The trade-off between wages and work conditions applies not only to workers but also to firms. Firms supplying bad jobs face a cost of improving their work conditions greater than the wage premia paid to workers. The standard hedonic wage theory has been challenged by follow-up models of equilibrium search, c.f. Burdett and Mortensen (1998), extending their wage dispersion feature to dispersion of utilities that depend on both pecuniary and non-pecuniary attributes; existing search frictions in matching workers to firms might then lead to equilibria with different configurations of wages and amenities, where the slope of the worker's indifference curve need not equal the slope of the wage-amenities relationship, c.f. Hwang et al (1998), or Lang and Majumdar (2004). Testing any of these theories, not to mention disentangle them, has proven quite difficult in practice, due to the general lack of suitable data. For instance, most research based on estimation of hedonic wage equations has not been able to account for unobservables in the worker and the firm's utility

	Wor	nen	Men	
	1989	1997	1989	1997
High Income	19.6	18.2	23.6	21
Flexible working hours	20.3	20.2	14.6	15.5
Good opportunities for advancement	23	20.2	24.3	20.1
Job security	58.7	57.7	55.5	55.4
Interesting Job	47.9	47.8	45.3	46.9
Allows to work Independently	29.1	31.3	33.4	33.4
Allows to help Other people	23.4	25.3	16.5	16.8
Useful to society	25.5	23.9	21.8	16.8

Table 1: Job values in OECD countries, 1989-1997

Source: Clark (2005), ISSP data; OECD countries are West Germany, UK, USA, Hungary, Italy, Netherlands, and Norway. For each aspect of job quality percentages saying "very important"

functions; estimation of duration models, as the proposed way to test equilibrium utility dispersion frameworks, faces similar problems: it is hard to pin down both observed and unobserved factors influencing worker-job separation hazards. Indeed, the empirical results obtained in this context so far are all over the map, with a typical trend of very small and/or statistically insignificant compensating wage differentials (CWD) obtained in conventional hedonic wage equation settings, whereas often very large point estimates of the workers' marginal willingness to pay (MWP) for amenities in equilibrium search-utility dispersion settings.

In this paper we propose a bridge between these competing explanations, using to that end uniquely suited Danish data. To our knowledge, this is the first study where we are able to control for both worker and firm time-invariant unobservables, on top of accounting for the sorting of workers across jobs according to their attitudes towards risk, in the conventional hedonic wage framework. We are then able to compare the range of our CWD estimates with duration model estimates obtained using the worker employment histories, as justified by the utility dispersion equilibrium-search framework. Subsequently, we attempt to rationalize our findings by means of a new theoretical model of job hazard premia and worker risk attitudes.

The paper is organised as follows. In Section 2 we give a brief overview of the CWD literature, focusing on earlier studies relevant in introducing our paper. Section 3 describes the data used in our empirical analysis and the construction of the work-place environment indicators. In Section 4 we present our econometric specifications. Section 5 discusses our findings, while section 6 devises a unified model of job hazard premia and risk preferences to explain the main empirical results. We summarize and conclude in Section 7.

2 Literature overview

Back in 1776, Adam Smith conjectured that, given a labour market equilibrium, people facing worse working conditions would obtain higher wages. The relevant theoretical framework for the analysis of compensating wage differentials CWD is provided by the hedonic wage models, initiated by Rosen (1974, 1986). In these models, perfect competition implies that workers' preferences for job attributes translate one-to-one into wage differences. Thus, job CWD, or, alternatively, worker marginal willingness to pay (MWP) for amenities, can be estimated by cross-sectional hedonic wage regressions, as Rosen (1974) and Rosen and Thaler (1975) propose. However, this method has not yielded strong or consistent evidence of compensating differentials, since estimates are typically of very small order of magnitude, if not statistically insignificantly different from zero, and/or wrong-signed. Various reasons for this failure have been identified. First, wages and job hazards may be regarded as endogenous variables in an individual working decision (e.g., Garen, 1988). Second, individual skills (especially: individual worker ability/productivity) and job amenities are typically unobserved, giving rise to an omitted variable bias (e.g., Brown, 1980; Duncan and Holmlund, 1983; Hwang et al., 1992). Third, since a simultaneous determination of job hazards and wages occurs in the establishments'/firms' profit maximization, errors in measuring the establishments' cost in providing amenities (e.g., unobserved establishment productivity) might generate further bias, e.g., Gronberg and Reed (1994), Hwang et al (1998), Lang and Majumdar (2004). These latter studies have recognized that the basic hedonic wage framework faces a fundamental problem since it uses static optimizing tools, while addressing what is inherently a dynamic process. Workers search for jobs that will provide higher utility, and guit whenever such an opportunity arises. If workers have positive preferences for some non-wage components, such models predict that in equilibrium the labour supply facing each establishment should be increasing in wages and non-wage components. By offering job bundles that provide higher utility to workers, firms can attract replacement hires more easily, and thereby reduce worker turnover. Thus, from the firms' perspective, wages and non-wage components, such as job safety, are instruments for achieving a profit maximizing labour supply. If the estimation of hedonic wage equations does not control for differences in firm cost efficiencies, then the error term in the hedonic wage equation will be positively correlated with the right hand side amenity variable; consequently, the standard CWD estimates will be biased.

Duncan and Holmlund (1983) reduce measurement error bias by matching working conditions derived from a dictionary of occupational titles with individually reported occupational hazards. Furthermore they use a longitudinal representative sample of workers from Sweden to put forward an empirical model of simultaneous changes in wages and working conditions. They argue that just as the change in wages, rather than their level, eliminates the confounding effect of unobserved worker heterogeneity that can be related to individual productivity, the formulation of change in the work environment indicators reduces the persistent tendencies of the respondents to apply different frames of reference to the questions regarding working conditions. Therefore an analysis that relates self-reported changes in working conditions to changes in wages will minimize the bias in the estimates of the CWD's (reducing both the omitted variable bias, and the measurement error). They group working condition variables into four broad categories: hours constraints, hard physical work, dangerous work and respectively, stressful work. Out of these, dangerous work and stressful work are shown to receive wage premia, while the others do not. Garen (1988) estimates wage premia for risk of fatality and injury allowing unobservables to affect earnings capacity and the returns to risk. As the endogeneity of job risk causes bias in the OLS estimation, the model is estimated with simultaneous equations and selection bias techniques. The results indicate that unobservable heterogeneity in the returns to risk is important, and that OLS underestimates the CWD for fatality and injury risk.

Dorman and Hagstrom (1998) addresses the difference between compensating wage differentials based on industry risk data and compensating wage differentials based on occupation risk data, showing that the relationship between wage compensation and risk at the workplace depends considerably on the risk measure one uses. They exploit the panel dimension of their data and extend Brown's (1980) approach in order to control for job, rather than individual, fixed effects, modelling the wage process as depending on unobserved ("productive") job specific characteristics. Moreover they incorporate a job-specific effect common to all amenities and independent of the wage. This second heterogeneity is motivated by the nature of the amenity variables used, which consist of self-reported measures of satisfaction with several dimensions of the job. They mention, inter alia, that with the exception of Duncan and Holmlund (1983), all the other wage-risk studies assigned average occupational/industry risk measures to individual workers, where besides ignoring individual risk measures, each degree of aggregation the data comes with can affect outcomes in a particular way.

Combining hedonic wage and collective bargaining models, Daniel and Sofer (1998) show the relevance of union power in the compensating wage differentials framework, using French cross-sectional data. Like Duncan and Holmlund (1983), they employ a group of binary individual indicators of working conditions, instead of average risk measures. They predict and confirm the coexistence of a negative relationship between wages and good work conditions for the whole sample (market effect), and a positive relationship for the highly unionized sector sample (union power effect).

Studies on CWD for job hazards usually do not explicitly recognize individual heterogeneity in risk preferences, in estimating average wage-hazard trade-offs. In practice, there are likely to be substantial differences in the workers' attitude toward risk. These differences in preferences may affect both the level of risk selected by the workers, as well as their associated wage risk trade-off. The standard hedonic wage model relies on the hypothesis that worker preferences affect the worker's choice of the job from the offer curve, assuming an indirect effect. A couple of studies using US data (e.g., Hersch and Viscusi, 2001, or DeLeire and Levy, 2004) examine heterogeneous worker attitudes toward health risks, which will affect their job safety performance as well as their job choice. Firms will change their offer curves in response to changes in riskiness. Differences in worker attitudes toward risk affect the shape of worker indifference curves as well as labor market offers. Hersch and Viscusi (2001) are in contrast with the conventional model of compensating differentials finding that smokers select riskier jobs but receive lower total wage compensation for risk than non smokers. The authors first develop a theoretical model in which worker risk preferences and job safety performance lead to smokers facing a flatter market offer curve than non smokers. The empirical result support the theoretical model, in fact smokers are injured more often than non smokers controlling for their job's objective risk and are paid less for these risks of injury. Smokers and nonsmokers are segmented labor market groups that face different labor market offer curves. DeLeire and Levy (2004) examine worker sorting across occupations in response to the risk of death on the job; they use family structure as a proxy for willingness to trade safety for wages to test the proposition that workers with strong aversion to this risk sort into safer jobs. They estimate a conditional logit model of occupation choice as a function of injury risk and other job attributes. The results confirm the sorting hypothesis: within gender, single moms and dads are the most averse to risk. Overall, their study shows that differences in the risk of death across occupations explain about one-quarter of occupational gender segregation.

A few empirical studies follow up on Grondberg and Reed's (1994) idea of estimating the marginal willingness to pay for job amenities using the relationship between the worker's job separation hazard and the worker's (multi-dimensional) job utility, for instance, van Ommeren et al (2000) or Dale-Olsen (2006). The latter takes into consideration the impact of search frictions on workers' MWP for safety, by using matched employer-employee Norwegian panel data covering the period 1994–96; he conducts classical hedonic wage regressions, as well as quit and duration regressions, but cannot account for typical omitted variable bias and sorting to the extent our study does, nor does he discuss comparatively the results obtained via the different specifications, attempting to find a unified theoretical explanation. Typically the range of estimates obtained by means of estimating MWP with duration frameworks is larger than those obtained with hedonic models, and might border on the extremely large; for instance, in Manning (2003) an implication is that workers in UK are willing to pay over 90% of their wage to switch from night-shift to day-shift jobs.

Finally, Dey and Flinn (2008)— in a specific context of search for wages and health insurance— and Bonhomme and Jolivet (2009) are examples where direct structural estimation of partial equilibrium search models is attempted. Bonhomme and Jolivet use a direct proxy for the costs of switching jobs with known pecuniary and nonpecuniary utility, by observing the worker's voluntary decision to change jobs in the ECHP data. They find support for the "pervasive absence of compensating wage differentials".

In our study we are able to replicate, improve and extend several of the empirical, and attempt to complement the main theoretical papers mentioned in this literature overview. Inter alia, our health and safety work environment conditions are selfreported by each individual worker, circumventing any problems due to assignment of average occupation/work conditions to individuals; the "soft", self-reported, data is merged with "hard", worker and firm register data, the difference in the data sources allowing us to work around other known problems where reporting bias would affect for instance both dependent and independent variables in our econometric specifications; our uniquely suited data allows us to take into account in conventional hedonic wage regressions i) both worker and firm time-invariant unobserved productivities, where we have enough job switchers for identification; ii) since we also observe work conditions that change for workers in the same job, we can also apply direct workerjob spell fixed effects; iii) we can infer worker risk attitudes from information on whether they smoke or have young children; since our data is longitudinal in nature and we have information on worker's employment duration along with her job utility components, we can at the same time estimate the worker's marginal willingness to pay for job amenities from job separation hazard specifications, wherein we are able to control for a large range of worker and job observed characteristics, allowing in addition for duration dependence and unobserved worker heterogeneity; finally, we attempt to rationalize our main findings from the empirical exercise by means of a new model of worker-job hazard premia, turnover and individual risk preferences.

3 Data description

Preparing for the empirical analysis in this paper, we merge two Danish datasets, through individual worker identifiers. First, we use a longitudinal representative panel data set, "The Danish Work Environment Cohort Study" (hereinafter, DWECS), collected every 5 years, from 1990 to 2005, by the National Research Center for the Working Environment, with the respondents individuals employed at the time, or within two months prior to the date of, the interview (October-December of the survey year). The survey questionnaire contains unusually detailed work environment hazard information, such as exposure to physical agents (noise, radiation, vibration, etc.), thermal fluctuations, chemical and biological agents, time-scheduling hazards (shift, night work, etc.), social environment indicators (participation and consultation with boss or co-workers and conflicts at work), job security perceptions, and indicators of general job satisfaction. Particular attention was paid to the representativeness of the cross-sectional worker sample in each wave, but also to ensuring the consistency of the panel dimension over time (about 5000 individuals are surveyed in all four waves). The questionnaire is described in detail in the Appendix.

Second, we use Statistics Denmark's exhaustive Integrated Labour Market Database (IDA), which comprises the entire (used as linked employer-employee) Danish population of individuals, and establishments (and, via establishments, the universe of firms, the unit used in our analysis), from 1980 to 2005. Danish administrative registers record individual annual earnings as well as many demographic characteristics (such as: age, gender, number of children, occupation, home municipality, work experience), as well as firm characteristics, such as employment size, industry etc. Tenure can be computed for each individual, down to year 1964. This dataset has been used, and thoroughly described, in many previous studies, including Mortensen (2003) or Buhai et al (2008).

Merging these two datasets, DWECS and IDA, is unproblematic since it is carried out on individual (anonymized) social security numbers, ie. "CPR"s.

3.1 Definition of work condition variables

The choice of explanatory variables in our context is determined by arguments from the large existent empirical literature on compensating wage differentials. Given the richness of our data, we identify 5 broad categories of adverse work conditions ¹. Firstly, we define a set of three binary variables that provide a subjective valuation of harms related to hazarduous work conditions, experienced at the workplace. Each of these variables is constructed from a six-point scale, in which the lowest category corresponds to the perception by a worker that a feature of working conditions is 'very much' an adverse factor at the workplace: we recode them as 1 when the worker is 'ever exposed'(scale 1-5) to this particular harm during her working time, and 0 if he/she is never exposed. For the other work conditions from below the variables are already dichotomous in the questionnare. Namely:

Phyharm takes value 1 if at the time of the interview the worker was exposed to: (i) noise so loud that he/she has to raise his/her voice to talk with other people (lnois6); or (ii) vibrations from hand tools (bvibr6); or (iii) vibrations from strike his/her whole body (hvibr6); or (iv) bad lighting (blight6); 0 otherwise.

Termharm takes value 1 if at the time of the interview the worker was exposed to: (i) temperature fluctuations (vtemp6); or (ii) coldness (work outdoor or in cold rooms) (cold6); (iii)or draft (draugh6); 0 otherwise.

Chemharm takes value 1, if at the time of the interview the worker was exposed to: (i) skin contact with refrigerants or lubricants (clean6); or (ii) solvent vapor (solve6); (iii) or passive smoke (psmoke6); 0 otherwise.

Next, we are able to consider the possible impact on the worker's wage of potentially undesirable work schedules. Specifically, we contruct a dummy variable $Work_flex_harm$ (we use also *shift*, interchangeably, later on in the estimation section) that takes value 1 if the individual experienced at least one of the following situations: "shift"=1 if the worker worked in shifts (either two or three shifts),

¹All our results generally hold if we use each very specific, narrowly-defined, work conditions, instead of the broadly-defined categories. Naturally, there is some further heterogeneity in those (e.g., vis-a-vis their individual statistical significance, when the broader category was statistically significant), which is however more difficult to interpret, both in the light of the existent literature, or simply intuitively, and, ultimately, less interesting. All empirical results using the narrowly-defined work environment proxies are available upon request.

0 otherwise; "night shift"=1 if the worker works in fixed night shifts, 0 otherwise; "evening shift"=1, if the worker works in fixed evening shifts, 0 otherwise.

Finally, we construct the variable *Jobsec*, that accounts for the worker's perception about her job (in)security. This takes value 1 if the worker mentions to worry about at least one of the following situations: (i)Losing job?; (ii) Transferred against will?;(iii) Made redundant because of new technology?, (iv) Difficult to find a new job?

3.2 Descriptive statistics

Since we are worried about unobserved non-market preferences of females that might induce further unobserved heterogeneity in our analyses, and obscure our testing of the existing CWD theories, we use only males in the empirical analyses that follow². In the empirical part we use a set of controls for individual worker characteristics, such as marital status, years of education, potential experience, and tenure. In our econometric specifications that account for sorting of workers across hazard regimes, according to their attitudes towards risk, we use information on whether the subject reports smoking ("smoke"), the presence of children in the household ("kids"), or her job satisfaction ("jobsat"). We also use a set of job attributes such as industry (ind1-ind11) and occupational dummies (occ1-occ10)—which are not presented in the summary statistics. In Table 2 we present summary statistics of the main variables in the merged IDA-DWECS dataset.

4 Econometric specifications

4.1 Hedonic wage equations

4.1.1 What has been done within the standard CWD context

The typical way of estimating hedonic wage equations has been through using simple cross-sectional (or pooled over several cross-sections) data and simple least squares as estimation technique, as below:

cross-sectional OLS :
$$y_i = \alpha + \beta X_i + \gamma Z_i + \varphi Q_i + \varepsilon_i$$

for each year, '90, '95, '00, '05.

pooled OLS:
$$y_i = \alpha + \beta X_i + \gamma Z_i + \varphi Q_i + \delta_{1990} + \delta_{1995} + \delta_{2000} + \varepsilon_i$$
 (1)

where y natural logarithm of hourly wages, X vector collecting individual characteristics (civil status, occupation, schooling, linear and quadratics in experience and tenure), Z firm related characteristics (firm size, industry), and Q work environment

 $^{^{2}}$ In fact, the empirical results obtained on the sample of females are virtually identical, which might be explained by the fact that in Denmark females do not face face all the typical child-bearingrelated absence problems etc., or, if anything, to an insignificant extent in this context. Nevertheless, for comparison with previous studies and for clarity, we report only the results for males.

Table 2: S	Summary	Statistics,	IDA-DWECS,	All Male
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Variable	Obs	Mean	Std. Dev.	Min	Max	Year
logwage	9731	5.150	0.295	4.319	6.034	90-05
educyears	11191	12.697	2.789	7	17	90-05
married	11191	0.507	0.500	0	1	90-05
ten	11191	5.276	5.638	1	40	90-05
workflex	8618	0.145	0.352	0	1	90-05
$_{\rm jobsec}$	8574	0.363	0.481	0	1	90-05
phyharm	8661	0.422	0.494	0	1	90-05
$\operatorname{termharm}$	8662	0.453	0.498	0	1	90-05
$\operatorname{chemharm}$	8690	0.319	0.466	0	1	90-05
noise	8656	0.323	0.468	0	1	90-05
$\operatorname{bodyvibr}$	8645	0.095	0.293	0	1	90-05
temp	5733	0.308	0.462	0	1	90-05
draug	8643	0.255	0.436	0	1	90-05
clean	8643	0.059	0.236	0	1	90-05
solvent	8669	0.067	0.250	0	1	90-05
losejob	8560	0.202	0.401	0	1	90-05
$\operatorname{transfer}$	8370	0.109	0.311	0	1	90-05
redund	8539	0.077	0.267	0	1	90-05
$\operatorname{diffnewjob}$	8522	0.205	0.403	0	1	90-05
shift	8618	0.110	0.313	0	1	90-05
evening	8618	0.018	0.132	0	1	90-05
night	8618	0.017	0.129	0	1	90-05
kids	7171	.455	.497	0	1	95 - 05
jobsat	11111	.05	.203	0	1	90-05
smoke	8962	.394	.488	0	1	90-05

related variables (which could be specific, or general work conditions proxies); δ are time effects and ε_i white noise.

For an undesirable job attribute, the hedonic wage theory predicts $\varphi > 0$. However, as discussed above, the empirical evidence on compensating wage differentials for job characteristics other than the risk of death is mixed. Several previous attempts have been made to solve this puzzle. First, estimates may suffer from sorting bias: workers choosing a job with a specific undesirable attribute are the ones with lower aversion for such an attribute (e.g., Kostiuk, 1990). Second, working conditions are endogenously determined: "richer" individuals might be more able to bargaining over working conditions than "poorer" individuals (e.g., Garen, 1988). Third, omitted variables can also lead to biased estimates due to the correlation between unobserved skills, individual productivities, and quality of working conditions (e.g., Brown, 1980, Duncan and Holmlund, 1983, Hwang et al,1992). Finally, when worker conditions are defined using average occupation (or industry) characteristics and then matched to individual workers, misclassification bias may arise.

We can deal with several of these criticisms above. One of them that was dealt with more than a quarter century ago, c.f. Duncan and Holmlund (1983), is to use individual work conditions, and to account for the worker's time-invariant unobserved heterogeneity by using individual FE regressions (or: first-differences OLS) instead of OLS, provided one has the suitable data for this exercise:

individual FE :
$$y_{it} = \alpha + \beta X_{it} + \gamma Z_{it} + \varphi Q_{it} + \mu_i + \varepsilon_{it}$$
 (2)

4.1.2 Accounting for both worker and firm unobservables

However, even after controlling for individual worker fixed effects as in (2) above, we might still have unobserved firm heterogeneity that could be connected to the working environment, and this might potentially bias our estimates. Provided one has linked employer-employee data with individually reported work conditions as well, we can go a step further than what has been done so far, namely to account for both worker and firm time-invariant unobservables, as below:

2-way FE:
$$y_{ijt} = \alpha + \beta X_{ijt} + \gamma Z_{jt} + \varphi Q_{ijt} + \mu_i + \psi_j + \varepsilon_{it}$$
 (3)

where μ_i worker fixed effect, ψ_j firm fixed effect for firm j; where worker i works in period t, and where the other variables are as defined above.

This estimation relies on the existence of "movers" across jobs, with mobility assumed to be exogenous, conditionally on the observed controls and on the timeinvariant unobservables. The estimation method is based on Abowd, Kramarz and Margolis (1999) (hereinafter AKM), with their technique update in Abowd, Creecy and Kramarz (2002).

In addition, since we observe the reported work conditions changing for workers that do not change jobs we can also estimate a within-job spell specification (a spell FE, in other words), which has not been encountered hitherto either, given the lack of such data (ideally, Duncan and Holmlund would have performed their first-differenced OLS within-job spells, not within-individual). Identification of the work environment parameter relies on variation of the workplace environment proxies within the same job.

within-spell:
$$\widetilde{y_{ijt}} = \beta \widetilde{X_{ijt}} + \gamma \widetilde{Z_{ijt}} + \varphi \widetilde{Q_{ijt}} + \widetilde{\varepsilon_{ijt}}$$
 (4)

with $\tilde{y}_{ijt} = y_{ijt} - \bar{y}_{ijt}$. A potential problem herein is that the estimation relies on "stayers" only; hence does not take into account the fact that stayers might be inherently different than movers, and thus the results not representative for the whole sample. Another problem is related to the fact that reporting within the same job of different conditions, at different points in time, might be influenced also by other factors, leading to potentially larger subjectivity bias.

4.1.3 Accounting for worker sorting based on risk preferences

The existing literature on CWD for job hazard does not explicitly acknowledge individual heterogeneity in preferences for risk in the estimation of average wage-risks trade-offs, but in practice considerable differences in individual attitudes towards risk exist. Additionally, in a situation in which workers' safety behavior is an important contributor to the riskiness of the job, the nature of the labor market opportunities may differ as well, c.f. Hersch and Viscusi (2001).

In general it is not possible to measure directly the worker's attitude towards risk, but proxies for that could be used; like Hersch and Viscusi the main proxy we use in our paper is the workers' reported smoking behavior³. Smokers jeopardize their health more than non smokers; this might be due to different reasons. First, smokers may value their health less than non smokers; second they might undervalue health losses; and third, they could underperceive health risks. In the existing literature, this was modelled either as due to differences in the underlying structure of preferences of smokers versus non smokers, or to the extent to which risk is individually perceived by the two groups of individuals (e.g., Manning et al.1991; Hersch and Viscusi, 1990 and 2001). The important implication from here is that, given that all workers in the market face the same offer curve, smokers will select a job associated to a greater job risk level than non smokers.

In order to account for heterogeneity in worker preference for risky jobs, we consider an endogenous switching regression model specification. For simplicity, hereinafter we exemplify only for the case where "smoking" is the proxy for the worker

³Hersch and Viscusi (1990), using a data set that allows to measure job risk perceived by individuals, as well as smoking and seatbelt use, find that cigarette smokers and nonseatbelt wearers receive a lower compensating differential for risk than nonsmokers and seatbelt wearers. In this paper we use as risk-loving proxy a dummy variable that takes value 1 if the individual smokes, and 0 otherwise. We complement this baseline specification with others in which selection into risky regimes can be influenced by being parents of small kids, or by the self-reported job satisfaction (while we recognize immediately the potential endogeneity of this last instrument in the selection equation, we also report these results, for robustness concerns).

risk profiles, while in the estimations we also report alternative specifications where we use smoking together with having young kids, and/or also with reported job satisfaction.

We are interested in the workers' wages in the two regimes, hazard and no-hazard. Let us focus here on shift and non-shift jobs, for clarity. Thus for each observation for now, we keep it simple and we consider the cross-sectional or pooled case, below we complicate with the case where we have repeated observations on workers and firms, we will have—:

$$y_{s} = \alpha + \beta X + \gamma Z + \varphi Q + \varepsilon_{s}$$

$$y_{ns} = \alpha + \beta X + \gamma Z + \varphi Q + \varepsilon_{ns}$$

$$S = \gamma K + \delta(y_{s} - y_{ns}) + \nu$$
(5)

where y_s is the wage in the shift-job, S is the shift choice that depends on the selection variables K, and the rest of variables are defined as above. $y_s - y_{ns}$ will capture the wage premium for shift jobs. K in the baseline case contains the worker's reported smoking status.

TBC XXX

This model can be estimated separately in two distinct stages or directly, using Full Information Maximum Likelihood (FIML). The advantage is that with the FIML the standard errors are already corrected in the final stage. The disadvantage is that there are severe computational problems when trying to implement FIML with unobserved worker, or with both unobserved worker and firm effects. A first strategy for estimation will first decompose wages via the 2-way AKM procedure, and thus discard both estimated worker and firm effects, (or, alternatively, only worker effects, if we use only individual worker fixed effects in decomposing wages a priori) to start with. We also simply use the data pooled, and apply FIML directly in (5). Alternatively, we proceed with estimating in two distinct stages, where in the first stage we take into account the selection based on worker time-invariant unobserved heterogeneity. The problem is the incidental parameter problem, which leads to considerable bias both under logit or probit FE when the time dimension is as small as in our case (4 waves), e.g. Greene (2004) and references therein. While the results are qualitatively similar in all these specifications, there are different quantitative ranges that we discuss in the interpretation of our findings.

TBC XXX

4.2 MWP from employment history analysis

We use worker employment histories, cf. Gronberg and Reed (1994), and follow-up papers. Define the job separation hazard h() of a worker with job utility u(w, q), where w is wage, q for simplicity a single nonpecuniary characteristic; δ is the exogenous probability of separation and λ_E is the probability of getting a job offer drawn from distribution F().

$$h(u(w,q)) = \delta + \lambda_E [1 - F(u(w,q))]$$

Then it is straightforward to show that

$$\frac{\partial h}{\partial q} = \lambda_E \frac{\partial [-F(u)]}{\partial u} \frac{\partial u}{\partial q}$$

and
$$\frac{\partial h}{\partial w} = \lambda_E \frac{\partial [-F(u)]}{\partial u} \frac{\partial u}{\partial w}$$

Hence, the worker's marginal preference, or "willingness" to pay for the job amenities will be given as a relationship between the worker-job hazard rate and the worker's job utility.

$$\frac{\frac{\partial h}{\partial q}}{\frac{\partial h}{\partial w}} = \frac{\frac{\partial u}{\partial q}}{\frac{\partial u}{\partial w}} = MWP$$

We estimate a proportional job separation hazard model, accounting for unobserved heterogeneity. Then, with Q the vector collecting all scalar amenities q, the hazard will be given by:

$$h(w_{ijt}, Q_{ijt}, T_{ijt}, \mu_i) = \frac{\exp\left(\alpha w_{ijt} + \beta Q_{ijt} + \gamma X_{ijt} + \psi_{T_{ijt}} + \mu_i\right)}{1 + \exp\left(\alpha w_{ijt} + \beta Q_{ijt} + \gamma X_{ijt} + \psi_{T_{ijt}} + \mu_i\right)} \tag{6}$$

We use a fully flexible baseline: full set of dummies ψ_T for every 5-year tenure level; to start, 2-mass point distribution for μ_i ; X_{ijt} includes education, industry and occupation (no time-varying covariates).

5 Discussion of empirical results

5.1 CWD estimates controlling for worker and firm fixed effects

Results for the estimations in (1)-(4) are presented in the corresponding columns of Table 3. Estimates for yearly cross-sectional OLS specifications are virtually identical to the OLS pooled specification, hence we do not report those.

We notice that the results in the first two columns, from the left, are very similar, while the results in the last two columns are again very similar. The most interesting is that, consistent across all these estimation methods, we find that the only job hazard relating to time flexibility is compensated for and that the estimate ranges between 4 and 6%, with the lower estimate obtaining when we control also for the firm unobserved effect, either by using a 2-way FE, AKM, specification, or by using a spell-FE specification.

Table 3: Pooled, Ind- FE, 2-way FE, spell-FE, ALL MALE

	<u>na 12,2</u>	·	<u></u>	
DEP.VAR (logwage)	pooled	INdFE	2wayFE	JODSPELL
	(1)	(2)	(3)	(4)
educyears	.016***	.019***	.079***	.088***
	(.001)	(.001)	(.032)	(.013)
married	.049***	.053***	.023***	.029**
married	(.006)	(.007)	(.0013)	(.014)
ten	006***	006***	00172	001
UCH .	(001)	(001)	(0031)	(003)
	(.001**	(.001***	0001***	(1000)
ten2	0001	0001	0001	0001
	(.00005)	(.00005)	(.00007)	(.00007)
\exp	.016***	.018***	.0142	.015***
	(.001)	(.001)	(.0167)	(.006)
exp2	0003***	0004***	00043***	0004***
-	(.00003)	(.00003)	(.00008)	(.00006)
phyharm	.009	.006	0.002	0008
P11, 1101 111	(.006)	(.006)	(.0106)	(.010)
tormharm	026***	094***	0.014	011
	020	(006)	(0.014)	(009)
1 1	001	(.000)	0024	005
chemharm	.001	002	.0034	.005
	(.006)	(.006)	(.0129)	(.009)
jobsec	010*	003	0.011	.014
	(.006)	(.006)	(.0095)	(.009)
workflex	$.064^{***}$.061***	$.0437^{***}$.047***
	(.009)	(.009)	(.0195)	(.0016)
Nobs	6549	6549	6549	6549

Note: Significance levels: *** 1%, **5%, *10%; robust standard errors in parentheses. Robust standard errors (500 repetitions) reported for two stage regressions. In the estimates we also control for a full set of occupation and industry indicators. We also present the correlation table of the estimated unobserved firm and worker fixed effects with the other variables (from specification (3)). In particular we are interested in the correlation between the two estimated unobserved effects, and in the correlation of each of these effects with the work environment proxies. These results are displayed in Table 4.

What is remarkable is that there is quite sizable negative correlation, in the order of -0.61 between the person fixed effect and the worker fixed effect, which is at odds with most findings in such decompositions⁴. One has to keep in mind however that our data is spaced every 5-years, and not annual, as most data hitherto used in suck AKM decompositions. The correlations of either of the estimated fixed effects with the work environment proxies is negligible.

TBC XXX

5.2 CWD estimates accounting for selection based on risk preferences

We start first by presenting in Table 5 some summary statistics of the main variables for the separate samples of smoker and non-smoker males in our data.

We do notice immediately that smokers earn slightly less, are less educated, but are equally likely to be married, and have similar tenure and experience at the job. Furthermore, on all job hazards they score higher. These descriptives thus already point into the direction of smokers potentially selecting themselves in more hazardous jobs, however, at least on average, they also seem to earn less. Before going to the FIML estimation pointed out above, we would like to actually see whether naively estimated CWDs, separately on the samples of smokers and non-smokers respectively, do show some differences. These results are presented below in Table 6, where we use the spell- fixed effect specification from above, (4). Consistent with the results using all the sample, from above, we find that only time-flexibility hazards are compensated for, and the point estimate for smokers being larger in magnitude than in the case of their non-smoking colleagues. It becomes interesting to actually estimate a switching regression model, as explained in the empirical specification section above.

The full estimates using the baseline selection model, which is using only the sorting according to the smoking behaviour are presented in Tables 7 to 10.

Our results with all these specifications point out to the fact that there is indeed selection, but of a different type than that envisaged in Hersch and Viscusi. Namely, smokers (or risk-lovers, more generally) negatively select in hazardous jobs, which means that the estimated sizable premia in the case of time-inflexibility ("shift" jobs) is really due to compensating wage differentials and not to risk preferences. This result is consistent with Lanfranchi et al (2002), who also looked at compensating wage differentials in the case of shift work, but are not completely consistent with the

⁴We will not interpret here this finding as apparent evidence of sizable negative assortative matching (NAM), given the ongoing literature that debates whether AKM can actually give the sign of the matching whatsoever.

findings of Kostiuk (1990), as that study found no selection whatsoever. Our premia range from 18 to 26% when we use the full information maximum likelihood specification to estimate the switching regression model⁵. In our first two specifications we exploit the fact that we can use an AKM decomposition (results are identical if only substract an estimated individual worker fixed effect), to subtract a priori the firm and worker fixed effect from the wages; in the second we use the pooled data, without controlling for any unobserved heterogeneity. The results seem to be roughly consistent across the alternative specifications in the selection equations as well, with the exception of the case where we also use job satisfaction. This is however the variable most likely to be endogenous to the worker's choice. One might also object to estimating a selection model *separately* for each of our 5 broad categories of work environment proxies; indeed, one can think that the choice comes with a bundle. In ongoing work we allow for a choice over all 5 non-pecuniary work environment dimensions, and find similar results.

TBC XXX

5.3 CWD estimates using the duration model

TBC XXX

6 Towards a new job hazard premia & risk preferences model

We start from the smoker risk attitude model and job compensation in Hersch and Viscusi (2001).

Thus, we denote the market opportunity locus as w(p, s), where p is job risk, and s smoking intensity (0 for nonsmokers). Assume.

$$w_p > 0, w_{pp} < 0, w_s \le 0$$

Further denote by $(p_2)p_1$ the risk chosen by (non)smokers, and assume without loss of generality $p_2 > p_1$; suppose now that $w(p_2, s) - w(0, s) < w(p_1, 0) - w(0, 0)$.

The story in Hersch and Viscusi (2001) is that if smokers and nonsmokers do indeed face the same offer curves, then $w(0,s) = w(0,0) \rightarrow w(p_2,s) < w(p_1,0)$. However, also by the same offer curve faced, $w(p_2,s) = w(p_2,0)$, hence in fact $w(p_1,0) > w(p_2,0)$, contradiction. In this case, one would not be able to offer the same offer wage curves for both smokers and non-smokers.

TBC XXX

⁵The alternative is to use a two-step model, in the spirit of a Heckman selection model. While that allows consideration of a FE logit or probit in the first stage, unfortunately, given our very short T, we face the incidental parameter problem, see for instance Greene (2004) for extensive discussions; we report results based on this two distict stages in Appendix B. TBC XXX. While the qualitative behavior of these estimates is identical to the ones obtained by accounting for selection by means of the FIML model, magnitude range is much smaller.

7 Summary and conclusions

We (re)demonstrate the importance of controlling for unobserved (time-invariant) individual heterogeneity in conventional hedonic wage equations, e.g. Duncan and Holmlund (1983), Hwang et al (1992). Controlling in addition also for unobserved time-invariant firm heterogeneity obtains largely similar results, although in a few cases the statistical significance of some job disamenities in the hedonic wage equations disappears, e.g. termical harm. Importantly, the results from the two-way FE techniques exactly hold also when using only the sample of workers who experience changes in work conditions within the same job spell, ie. the "stayers". The static hedonic wage theory is directly valid in their case since changing work conditions in the same job trace the workers' indifference curves.

The only work environment conditions compensated for by wage premia (in our preferred estimates, the 2-way fixed effects) are the ones relating to flexibility in the working time, found important in most previous studies, eg. Kostiuk (1990), Manning (2003): "working in irregular shifts", "working in the evening", "working at night" No other work environment dimension pays a hazard premium, once we take into account both worker and firm unobserved heterogeneity, which is at odds with most previous CWD estimation papers, including the only other longitudinal study, Duncan and Holmlund (1983). However, these empirical methods, call them "upgraded hedonic wage equations", use strong assumptions: either exogenous switches (the case of the 2way-FE), or the subsample of individuals who never switch jobs (within-spell).

Allowing for heterogeneous risk preferences, we find that shift workers prefer to avoid shift work and day-time workers prefer day-time jobs. If we allow for the hazard premia to vary by smoking status (or other proxies such as having young kids), we obtain that smokers are compensated by wage hazard premia, in contrast to the result obtained by Hersch and Viscusi (2001). We show that wage premia for shift work are heavily underestimated without accounting for this selection (our favorite estimates are 18-26%, although in the two-stage models they are about 10%, whereas in the models not accounting for selection the premia are 4 to 6%). These results are fully consistent with Lanfranchi et al (2002), and partially with Kostiuk (1990). We also show that there is selection (mostly negative as above, positive only for termical harm) for the other work environment proxies, but the wage premia are small and/or statistically insignificant.

TBC MWP Hazard Results XXX

TBC Job hazard premia, job-worker separation, and worker risk profiles theory XXX

References

Abowd J., F. Kramarz F. and D. Margolis (1999), "High Wage Workers and High Wage Firms", *Econometrica*, 67(2), pp.251-334

- Bonhomme, S. and G. Jolivet (2009), "The Pervasive Absence of Compensating Differentials", *Journal of Applied Econometrics*, forthcoming
- Brown, C. (1980), "Equalizing differences in the labor market", *Quarterly Journal* of Economics, 94,113-34
- Buhai, I. S, M. Portela, C. Teulings and A. van Vuuren (2008), "Returns to Tenure or Seniority? ",TI DP 08-010/3, IZA DP 3302
- Burdett, K. and D. Mortensen (1998), "Wage Differentials, Employer Size, and Unemployment," *International Economic Review*, vol. 39(2), pp.257-73.
- Clark, A. (2005), "Your Money or your life: Changing job Quality in OECD Countries", *British Journal of Industrial Relations*, 43, 377-400.
- Dale-Olsen, H. (2006), "Estimating Workers' Marginal Willingness to pay for Safety using Linked Employer-Employee Data", *Economica*, 73, 99-127
- Daniel, C. and C. Sofer (1998), "Bargaining Compensating Wage Differentials and Dualism of the Labor Market. Theory and Evidence from France", *Journal* of Labor Economics, 16(3), 546-75
- Dey, M. and C. Flinn (2008), "Household search and health insurance coverage", Journal of Econometrics, 145(1-2), pp. 43-63
- **DeLeire, T. and H. Levy** (2004), "Worker Sorting and the Risk of Death on the Job", *Journal of Labor Economics*, 22(4), 925-953
- **Dorman, P. and P. Hangstrom** (1998), "Wage compensation for dangerous work revisited", *Industrial and Labor Relations Review*, 52,116-35
- Duncan, G. and B. Holmlund (1983), "Was Adam Smith Right after all? Another Test of the Theory of Compensating Differentials", *Journal of Labor Economics*, 1,366-79
- Garen, J. (1988), "Compensating wage differentials and the endogeneity of job riskness", *Review of Economics and Statistics*, 70, 9-16
- **Greene**, W. (2004), "The behaviour of the maximum likelihood estimator of limited dependent variable models in the presence of fixed effects", *Econometrics Journal*, vol 7, 98-119
- Gronberg T.J. and R.W. Reed (1994), "Estimating Workers' Marginal Willingness to Pay for Job Attributes Using Duration Data", *The Journal of Human Resources*, 29(3), pp. 911-931
- Hersch, J. and W.K. Viscusi (1990), "Cigarette Smoking, Seatbelt Use and Differences in Wage Risk Trade-offs", *The Journal of Human Resources*, 25(2), 202-227
- Hersch, J. and W.K. Viscusi (2001), "Cigarette Smokers as Job Risk Takers", The Review of Economics and Statistics, 83(2), 269-280.

- Hwang, H., W. Reed and C. Hubbard (1992), "Compensating Differentials and Unobserved Productivity", *Journal of Political Economy*, 100, 835-58.
- Hwang, H., D. Mortensen and W. Reed (1998), "Hedonic Wages and Labor Market Search", *Journal of Labor Economics*, 16,815-47.
- Kostiuk, F. (1990), "Compensating differentials for shift work", Journal of Political Economy, 98 (5), pp. 1055–1075.
- Lanfranchi J., H. Ohlsson H. and A. Skalli (2002), "Compensating wage differentials and shift work preferences ", *Economics Letters*, 74(3), pp. 393-398
- Lang, K. and S. Majumdar (2004), "The Pricing Of Job Characteristics When Markets Do Not Clear: Theory And Policy Implications", *International Economic Review*, vol. 45(4), pp.1111-1128.
- Manning, W.G., E.B. Keeler, J.P. Newhouse, E.M Sloss and J. Wasserman (1991), "The Cost of Poor Health Habits", Cambridge, Harvard University Press
- Manning, A. (2003), "Monopsony in Motion: Imperfect Competition in Labor Markets", Princeton University Press
- Rosen, S. (1974), "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition", *Journal of Political Economy*, 82,34-55
- Rosen, S. (1986), "The Theory of Equalizing Differences", in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics*, 1(2),641-92, Amsterdam:Elsevier Science
- van Ommeren J., G. van den Berg and C. Gorter (2000), "Estimating the Marginal Willingness to Pay for Commuting", *Journal of Regional Science*, 40 (3), pp.541-563

A DWECS questionnaire overview

- Are you exposed to:
 - noise so loud you have to raise your voice to talk with others?
 - vibrations from hand tools?/ vibrations that strike your whole body?
 - temperature fluctuations ? coldness (work outdoor or in cold rooms)?/ draught ?
 - skin contact with cleaning materials or disinfectants? /solvent vapour?
 - passive smoke ? / bad lighting
- Is your work physically demanding?
- Does your work require that you repeat the same work tasks many times per hour?
- Do you worry about the following situation:
 - losing your job?
 - transfer against your will?
 - made redundant because of new technology?
 - difficulty to find a new job?
- How are your working hours normally placed?
 - shift (1 if the workers works on two or three shifts or working hours are
 - irregularly placed during the week according to a rotation, 0 otherwise)
 - night (1 if the worker works on fixed night shift, 0 otherwise)
 - evening (1 if the worker works on fixed evening shift, 0 otherwise).

	resid													
	firmeff												Т	-0.00002
	personeff											1	-0.6101	0.00001
	workflex										1	0.0046	-0.0011	0.00002
- L L	jobsec									1	0.0296	0.0369	-0.0144	0.00002
	chemharm								1	0.0683	0.1016	-0.0406	0.0115	-0.00007
-conplitioner	termharm							1	0.2347	0.0876	0.1239	-0.0318	0.0177	-0.00001
e zwayru	phyharm						1	0.3295	0.2107	0.0603	0.1225	-0.0473	0.0154	0.0001
	$\exp 2$					Π	-0.0484	-0.1182	-0.0889	0.0758	-0.06	0.1313	0.0235	0.00003
COLLETAN	exp				Η	0.9645	-0.0326	-0.0912	-0.089	0.0712	-0.0623	0.1289	0.0287	0.00004
T OTOPT	ten2			1	0.3296	0.3322	-0.013	-0.0248	-0.0077	0.0534	-0.0308	0.0899	0.02	0.0004
	ten		Ξ	0.9312	0.3689	0.3494	-0.0091	-0.019	-0.0091	0.0531	-0.0301	0.1045	0.0196	0.00001
	logwage	1	0.1085	0.0833	0.1771	0.1389	-0.1053	-0.1394	-0.0942	-0.035	-0.0181	0.2828	0.2754	0.224
		logwage	ten	ten 2	\exp	$\exp 2$	phyharm	termharm	$\operatorname{chemharm}$	jobsec	workflex	personeff	firmeff	resid

ΨĮ	
ALL 1	
Estimates:	
2 wav FE	
Table	
Correlation	
Table 4:	

	ALL	SMOKERS	NSMOKERS
wage(kr)	174.27	167.45	184.70
educyears	12.70	12.38	13.24
married	0.51	0.52	0.55
ten	5.28	5.46	5.42
\exp	17.81	18.13	18.13
workflex	14.52	17.68	12.45
jobsec	36.28	39.53	34.13
phyharm	42.17	46.71	39.19
$\operatorname{termharm}$	45.3	50.72	41.75
$\operatorname{chemharm}$	31.91	36.61	28.82
Nobs	8618	3365	5163

Table 5: Smokers vs. NSmokers: Descriptive Stats

 Table 6: All vs. Smoker vs. NSmoker, Within job spell

 ALL
 SMOKERS
 NSMOKERS

$\begin{array}{ c c c c c c c c c c c c c c c c c c c$		ALL	SMOKERS	NSMOKERS
educyears $.088^{***}$ $.099^{***}$ $.086^{***}$ $(.013)$ $(.017)$ $(.020)$ married $.029^{**}$ $.027$ $.041^{**}$ $(.014)$ $(.022)$ $(.020)$ ten $.001$ $.007$ 0008 $(.003)$ $(.005)$ $(.004)$ ten2 0001^* 00006 0002^{**} $(.0007)$ $(.0001)$ $(.0001)$ exp $.015^{***}$ $.043^{**}$ $.013^{**}$ $(.006)$ $(.018)$ $(.006)$ exp2 0004^{***} 0004^{***} $(.0006)$ $(.001)$ $(.0008)$ phyharm 0008 010 $(.010)$ $(.015)$ $(.014)$ termharm 011 020 $(.009)$ $(.014)$ $(.013)$ chemharm $.005$ $.015$ $(.009)$ $(.014)$ $(.013)$ workflex $.047^{***}$ $.057^{**}$ $.048^{**}$ $(.016)$ $(.027)$ $(.022)$ Nobs 6549 2702 3832		(1)	(2)	(3)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	educyears	.088***	.099***	.086***
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(.013)	(.017)	(.020)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	married	.029**	.027	.041**
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(.014)	(.022)	(.020)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	ten	.001	.007	0008
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(.003)	(.005)	(.004)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$ ext{ten2}$	0001*	00006	0002**
$\begin{array}{cccccccccccccccccccccccccccccccccccc$		(.00007)	(.0001)	(.0001)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	\exp	.015***	.043**	.013**
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(.006)	(.018)	(.006)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	$\exp 2$	0004***	0004***	0004***
$\begin{array}{c ccccc} \mbox{phyharm} &0008 &010 & .005 \\ (.010) & (.015) & (.014) \\ \mbox{termharm} &011 &020 &004 \\ (.009) & (.014) & (.013) \\ \mbox{chemharm} & .005 & .015 &010 \\ (.009) & (.014) & (.014) \\ \mbox{jobsec} & .014 &004 & .012 \\ (.009) & (.014) & (.013) \\ \mbox{workflex} & .047^{***} & .057^{**} & .048^{**} \\ (.016) & (.027) & (.022) \\ \mbox{Nobs} & 6549 & 2702 & 3832 \\ \end{array}$		(.00006)	(.0001)	(.00008)
$\begin{array}{cccccccccccccccccccccccccccccccccccc$	phyharm	0008	010	.005
$\begin{array}{c ccccccccccccccccccccccccccccccccccc$		(.010)	(.015)	(.014)
$\begin{array}{c} (.009) & (.014) & (.013) \\ (.013) & (.013) \\ (.014) & (.013) \\ (.009) & (.015) &010 \\ (.009) & (.014) & (.014) \\ (.013) \\ \\ \mbox{workflex} & .047^{***} & .057^{**} & .048^{**} \\ (.016) & (.027) & (.022) \\ \hline \mbox{Nobs} & 6549 & 2702 & 3832 \\ \end{array}$	$\operatorname{termharm}$	011	020	004
$\begin{array}{c cccc} chemharm & .005 & .015 &010 \\ (.009) & (.014) & (.014) \\ \\ jobsec & .014 &004 & .012 \\ (.009) & (.014) & (.013) \\ \\ workflex & .047^{***} & .057^{**} & .048^{**} \\ (.016) & (.027) & (.022) \\ \hline \\ Nobs & 6549 & 2702 & 3832 \\ \hline \end{array}$		(.009)	(.014)	(.013)
$(.009)$ $(.014)$ $(.014)$ jobsec $.014$ 004 $.012$ $(.009)$ $(.014)$ $(.013)$ workflex $.047^{***}$ $.057^{**}$ $.048^{**}$ $(.016)$ $(.027)$ $(.022)$ Nobs 6549 2702 3832	$\operatorname{chemharm}$.005	.015	010
jobsec $.014$ $(.009)$ 004 $(.014)$ $.012$ $(.013)$ workflex $.047^{***}$ $(.016)$ $.057^{**}$ $(.027)$ $.048^{**}$ $(.022)$ Nobs 6549 2702 3832		(.009)	(.014)	(.014)
workflex $.047^{***}$ $(.016)$ $.057^{**}$ $(.027)$ $.048^{**}$ $(.022)$ Nobs 6549 2702 3832	$_{ m jobsec}$.014	004	.012
workflex $.047^{***}$ $.057^{**}$ $.048^{**}$ (.016)(.027)(.022)Nobs654927023832		(.009)	(.014)	(.013)
(.016) (.027) (.022) Nobs 6549 2702 3832	workflex	$.047^{***}$.057**	.048**
Nobs 6549 2702 3832		(.016)	(.027)	(.022)
	Nobs	6549	2702	3832

Note: Significance levels: *** 1%,**5%, *10%; robust standard errors in parentheses. Estimations also use a full set of occupation and industry indicators

SEL. EQ	SHIFT	JOBSEC	PHY	TERM	CHEM
smoke	0.109**	0.058^{*}	0.087**	0.044	0.104***
	(0.038)	(0.027)	(0.031)	(0.032)	(0.029)
educyears	-0.030***	-0.018**	-0.009	-0.017^{*}	-0.010
	(0.008)	(0.006)	(0.007)	(0.007)	(0.007)
married	-0.111*	0.046	0.010	-0.048	-0.088*
	(0.046)	(0.035)	(0.036)	(0.036)	(0.037)
\exp	-0.008	-0.015*	0.023**	0.031^{***}	-0.014
	(0.009)	(0.007)	(0.007)	(0.007)	(0.007)
$ ext{ten}$	-0.005	-0.001	0.004	-0.001	0.001
	(0.011)	(0.008)	(0.008)	(0.008)	(0.008)
WAGE EQ0	· · ·	Regin	ne 0 (Dep V	ar:lnwage0)	
educyears	0.045^{***}	0.045^{***}	0.044***	0.044***	0.044^{***}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
married	0.048^{***}	0.047^{***}	0.055^{***}	0.050^{***}	0.049^{***}
	(0.003)	(0.004)	(0.005)	(0.004)	(0.004)
\exp	0.028^{***}	0.028^{***}	0.029^{***}	0.027^{***}	0.028***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
ten	0.002^{**}	0.002^{*}	0.002^{*}	0.001	0.002**
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
WAGE EQ1		Regin	ne 1 (Dep V	ar:lnwage1)	
educyears	0.046***	0.046***	0.045***	0.044^{***}	0.046***
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
married	0.060^{***}	0.038^{***}	0.035^{***}	0.039^{***}	0.054^{***}
	(0.009)	(0.006)	(0.005)	(0.005)	(0.007)
\exp	0.027^{***}	0.027^{***}	0.025^{***}	0.029^{***}	0.027^{***}
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
$ ext{ten}$	-0.000	0.001	0.001	0.002	-0.000
	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)
rho0	-0.17	-0.59***	0.578***	-0.067	-0.416***
rho1	76***	-0.75***	-0.499***	0.588^{***}	-0.792***
CWD(lnW1-lnW0)	26.6	16.10	0.86	-0.73	16.8
Nobs	6534	6534	6534	6534	6534

Table 7: FIML switching regression model, unobserved ind. and firm FE handled, baseline spec

 Note:
 Significance levels:
 *** 1%,**5%, *10%; robust standard errors in parentheses.
 Estimations also use a full set of occupation and industry indicators.

Table 8: FIML with unobservables handled a priori, alternative specs

		SHIFT	JOBSEC	PHY-H	TERM-H	CHEM-H
Baseline: smoking	rho0	17	59***	.578***	067	416***
is the exclusion	rho1	76***	75***	499***	$.588^{***}$	792***
restriction	E(nlw1)- $E(lnw0)$	26.6	16.10	0.86	-0.73	16.8
1) Any-kid is added to	rho0	728***	.361**	.531***	028	524**
baseline selection eq.	rho1	239***	.098	429	.638	.67***
as excl. restriction	E(lnw1)- $E(lnw0)$	23.2	4.1	-0.5	-8.3	-8.9
2)Job satisfaction is	rho0	171	.183	.559***	011	.372***
added to baseline select.	rho1	767***	.352***	.565***	.61	.541***
eq. as exclusion restriction	E(lnw1)- $E(lnw0)$	26.5	-5.9	11.8	-7.9	-8.9
3) like 1) with job	rho0	.255	.463***	.567***	.21	.516***
satisfaction added to the	rho0	735***	.314***	.468***	.595	.665***
baseline selection equation	E(lnw1)- $E(lnw0)$	21.3	-7.4	-10.1	-8.9	-13.6

Note: Significance levels: *** 1%,**5%, *10%; robust standard errors in parentheses. Control variables as in the corresponding, baseline specification, previous table.

SEL. EQ	\mathbf{SHIFT}	JOBSEC	PHY	TERM	CHEM
smoke	.053*	.065*	.100***	.026**	.080**
	(.03)	(.030)	(.028)	(.013)	(.027)
educyears	036***	020**	007	032***	015*
	(.008)	(.006)	(.006)	(.006)	(.007)
married	115**	.047	008	063***	109**
	(.044)	(.035)	(.035)	(.031)	(.036)
\exp	007	014*	.019**	.008	010
	(.009)	(.007)	(.007)	(0.006)	(.007)
ten	.006	004	-0.0001	0004***	.002
	(.010)	(.008)	(.008)	(.0001)	(.008)
WAGE EQ0		Regi	me 0 (Dep	• Var:lnwage0)	
educyears	.018***	.015***	.015***	019***	.016***
	(.001)	(.002)	(.002)	(.004)	(.002)
married	.055***	.051***	.063***	018	.058***
	(.007)	(.009)	(.009)	(.019)	(.009)
\exp	.017***	.017***	.018***	.009***	.018***
	(.001)	(.002)	(.002)	(.004)	(.002)
ten	.006***	.006**	.007***	011***	.007***
	(.002)	(.002)	(.002)	(.004)	(.002)
WAGE EQ1		Regi	me 1 (Dep	Var:lnwage1)	
educyears	.013**	.012***	.013***	00017	.013***
	(.004)	(.002)	(.002)	(.004)	(.002)
married	.046*	.047***	.017	.044***	.019
	(.019)	(.011)	(.011)	(.018)	(.013)
\exp	.011***	.011***	.019***	.037***	.014***
	(.003)	(.002)	(.002)	(.004)	(.002)
ten	.011**	.006**	.005	.028***	.005
	(.004)	(.002)	(.002)	.004	(.003)
rho0	-0.74**	0.36***	0.54^{***}	no conv.	-0.74***
rho1	-0.22	0.62^{***}	0.77^{***}	no conv.	0.78^{***}
$CWD(\ln W1 - \ln W0)$	18.9	-22.8	-31.2	no conv.	- 17.8
Nobs	6654	6680	6736	6736	6789

Table 9: FIML switching regression, pooled, baseline spec

Note: Significance levels: *** 1%, **5%, *10%; robust standard errors in parentheses. Estimations also control for a full set of occupation and industry indicators.

		SHIFT	JOBSEC	PHY-H	TERM-H	CHEM-H
	rho0	74**	.36***	.54***	n.c.	74***
Baseline	rho1	.22	.62***	.77***	n.c.	.78***
	E(nlw1)- $E(lnw0)$	18.9	-22.8	-31.2	n.c.	-17.8
1) Any-kid is added to	rho0	.231**	.334***	778***	n.c.	778***
baseline selection eq.	rho1	299	.771***	.858	n.c.	.857***
as excl. restriction	E(lnw1)- $E(lnw0)$	13.2	29.6	27.6	n.c.	27.5
2)Job satisfaction is	rho0	329**	.398***	726***	.421***	726**
added to baseline select.	rho1	255	.575***	.779***	.659***	.779***
eq. as exclusion restriction	E(lnw1)- $E(lnw0)$	14.3	-20.7	-17.8	-25.1	-17.8
3) like 1) with job	rho0	.283**	.407***	.311***	.302***	.311***
satisfaction added to the	rho1	262	.776***	.859***	.753***	.859***
baseline selection equation	E(lnw1)- $E(lnw0)$	12.3	-30.4	-39.3	-26.1	-39.2

Table 10: FIML switching regression pooled, alternative specs

Note: Significance levels: *** 1%, **5%, *10%; robust standard errors in parentheses. Control variables as in the corresponding, baseline specification, previous table.