

The Pervasive Absence of Compensating Differentials*

Stéphane Bonhomme[†]
Université de Paris I,
CREST-INSEE, Malakoff,
and CEMFI, Madrid

Grégory Jolivet[‡]
Université de Paris I,
CREST-INSEE, Malakoff

January, 2005

STILL PRELIMINARY AND INCOMPLETE

Abstract

So far, the theory of compensating differentials on the labor market has not met unambiguous empirical (in)validation. While regression estimates yield inconclusive correlations between wages and non-wage job characteristics, estimates of duration models show that amenities have a significant (decreasing) effect on job hazard rates. We show that these two results are not contradictory in the presence of high mobility costs as individual preferences are not necessarily reflected in cross-section data. To this end, we develop a model of wages, amenities and job-to-job mobility with two main features. First, a twofold heterogeneity is accounted for. Using the panel dimension, we can control for both the “productivity” and “subjectivity” of workers. Second, we construct a selection model of voluntary job change, for which the heterogeneity distributions provide a natural exclusion restriction. In the three countries we study, our estimates exhibit a systematic and significant compensation for amenities such as the type of work or working conditions. We empirically prove these strong preferences for amenities to be consistent with very weak compensating differentials in cross-section.

JEL codes: C33-35, J31-33, J63 and J81.

Keywords: Compensating differentials, job mobility, amenities, unobserved heterogeneity.

*Repeated conversations with Jean-Marc Robin led to significant improvements in this paper. We would also like to thank Manuel Arellano, Pierre Cahuc, Laurent Gobillon, Cédric Houdré, Francis Kramarz, Guy Laroque and Gerard Van den Berg as well as seminar participants at CEMFI, CREST and Tinbergen Institute for their comments and remarks. The usual disclaimer applies.

[†]CEMFI, Casado del Alisal, 5, 28014 Madrid, Spain. E-mail: bonhomme@cemfi.es

[‡]CREST-INSEE, 15 boulevard Gabriel Péri, 92 245 Malakoff Cedex, France.
E-mail: gregory.jolivet@ensae.fr

1 Introduction

Following Adam Smith (*An Inquiry Into the Nature and Causes of the Wealth of Nations*, Book I, Chapter 10) many researchers in economics have tried to test the appealing idea of compensating differentials on the labor market. In his classic exposition, Smith (1776) claimed that competition between firms and between workers forces the utilities of all the jobs in the labor market to be equal in the long run. Differences in wages must thus be compensated by opposite differences in non-wage job characteristics, such as working conditions. Rosen (1974, 1986) formalized this idea, building a model where jobs are bundles of multiple characteristics with implicit, or *hedonic*, prices.

The theory of compensating differentials has strong economic consequences, as it asserts that jobs are not necessarily ranked according to their monetary characteristics. Therefore, conclusions about the labor market based on the wage alone can be misleading. In cross-section, the theory implies that earnings inequality overstates inequality in the returns to work.¹ As for labor market dynamics, amenities can enter workers' mobility decisions and explain part of the job-to-job transitions associated with wage cuts. These implications motivate the need for empirical validation of the theory. So far, empirical studies have followed two different paths. The purpose of this paper is to reunite both trends in a model accounting for wages, amenities and job mobility.

The first generation of works on compensating differentials is based on cross-sectional hedonic regressions. In cross-section, the wage is expected to be negatively correlated to non-wage job characteristics, or *amenities*.² The general conclusion of this literature, though, is that estimates from wage regressions are likely to be severely biased.

The heterogeneity of workers' productivity is one source of bias. If most productive workers have both higher wage and better working conditions, say, then an observed positive wage/ amenity correlation is not contradictory to the existence of compensating differentials at the individual level (Hwang, Reed and Hubbard, 1992). Another source of heterogeneity lies in workers' subjectivity when using data on satisfaction with a non monetary aspect of the job. Two influential studies argue that panel data can help reducing the size of the heterogeneity bias. Using longitudinal data, Brown (1980) and Duncan and Holmlund (1983) estimate hedonic wage regressions in first differences. However, their evidence of compensating differentials in cross-section is mixed.

The second generation of tests of the theory, starting with Gronberg and Reed (1994), offers an explanation for the inconclusive results of hedonic wage regressions. Their main argument comes from the job search literature. If the labor market is

¹On the relationships between these two notions of inequality, see Hammermesh (1999).

²In this paper, amenities are implicitly assumed to be positively valued by workers. Non-wage job characteristics which affect negatively workers' utility are called disamenities.

characterized by the presence of informational frictions, then it may be optimal for a productive firm to post job offers with both high wage and good amenities, in order to attract workers, either unemployed or working at a less productive firm. Consequently, even if workers value both the wage and non-wage characteristics of their jobs, wages and amenities can be positively correlated in cross-section.³

In this literature, the parameter of interest is not the market return to a given amenity, but the Marginal Willingness to Pay (MWP) for this amenity defined as the ratio of the marginal utility of the amenity over the marginal utility of the wage. Gronberg and Reed (1994) show that this parameter can be estimated using transition data, as jobs with higher wages or better amenities are expected to last longer if quits are voluntary.⁴ Simulating data from a simple job search model, they show that hedonic regression estimates can be as low as one fourth of the true MWP. Employing the same method, Van Ommeren, Van den Berg and Gorter (1999) estimate a MWP for commuting distance which is twice as large as the coefficient of the hedonic regression.

In this paper, we incorporate some key features of these two literatures into a general model of wages, amenities and job-to-job mobility. As Brown (1980) we use Panel data to overcome the problem of individual heterogeneity. As Duncan and Holmlund (1983), we dispose of self-reported data on satisfaction with several dimensions of the job. These authors claim that panel data allows to reduce the bias which arises from workers' subjectivity, as measurement error is likely to be highly correlated over time. Generalizing this insight, we allow for two types of heterogeneity. The "productive" heterogeneity governs the wage/ amenity process, the "subjective" one rules satisfaction with a particular non-wage characteristic.

Job-to-job transitions are the keystone of the model. Consistently with Gronberg and Reed (1994), we assume that both wages and amenities influence quit decisions. However, our approach differs from theirs in several important aspects. First, we augment their framework by modeling explicitly the wage/ amenity offer processes. We are thus able to isolate the effects of the current wage and amenity on mobility, which Gronberg and Reed model and estimate, from the effect of wage and amenity offers, which they do not. Therefore, we need to identify and estimate a censored regression model, for which exclusion restrictions are required. Our identification strategy at this point relies on the two types of unobserved heterogeneity identified from the wage and amenity repetitions. We interpret this heterogeneity as the quality of a given firm/ worker match. Job offers are assumed independent of the current values of the wage and the amenity, conditional on the "productive" and "subjective"

³Hwang, Mortensen and Reed (1998) build an on-the-job search model where jobs are characterized by their wage and a non-wage characteristic. They show that wages and amenities can be positively correlated if firms are heterogeneous with respect to their production cost of the non-wage characteristic. Lang and Majumdar (2004) obtain the same result with a non-sequential search framework, in the case where both workers and firms are homogeneous.

⁴The assumption of an exogenous separation rate is fundamental in this approach. See Gronberg and Reed (1994), footnote 4.

quality of the current job.

Second, our data allows us to focus on voluntary job-to-job transitions, where the individual reports that her new job is “better”, in some sense, than her previous one.⁵ We independently study the voluntary transitions and the involuntary ones, such as layoffs. We model job-to-job mobility decisions that satisfy a generalized reservation wage property. Our two measures of Marginal Willingness to Pay, in the current job (denoted as MWP) and in job offers (MWP^*), are obtained as ratios of elasticities of the reservation wage.

We estimate the model for three countries and six different amenities separately. Our results show high and significant MWP 's, in accord with the intuition but less so with the literature. Moreover, for some characteristics such as the type of work and working conditions, we also find large and significant MWP^* 's. For these amenities, the impact of a lower offered satisfaction value is found equivalent to a 20-40% increase in the reservation wage.

We then compare these estimates to the results of hedonic wage regressions for job changers. Our model allows us to analytically decompose the wage differential for “good” and “bad” amenities, and show that it crucially depends on two parameters: the individual valuation of the amenity, and the explanatory power of wage offers in job mobility. We interpret this second term as reflecting mobility costs on the labor market. Empirically, we find that both the wage and amenities explain little of job mobility. Consequently, in cross-section, the effect of wage/amenity compensation can be dramatically reduced. Then, compensating differentials may appear quite small, or even wrong-signed, in wage regressions, despite strong individual preferences for non-wage characteristics.

The outline of the paper is as follows: we first present our data in section 2, and compute several descriptive statistics which provide informal evidence that the amenities we study in this paper have an impact on voluntary job mobility and influence workers' behavior. In sections 3 to 4, we present the model, and discuss identification and estimation issues. Section 5 shows the estimation results. Section 6 explains why hedonic wage regressions' estimates are likely to yield ambiguous results in economies where mobility costs are high and heterogeneous. Lastly, section 7 concludes.

2 Job mobility, wages and amenities: First empirical evidence

In this section, we conduct a simple descriptive analysis of a multi-country sample of individual transitions on the labor market. This allows us to emphasize a number of salient facts about workers' mobility, wages and non-wage job characteristics that will motivate our study. First, we present our data and describe the specific variables we will use for the analysis of job mobility and amenities.

⁵See Groot and Verbene (1997) and Villanueva (2004) for examples where the effects of non-wage job characteristics on voluntary mobility are studied.

2.1 The ECHP

We use the European Community Household Panel (ECHP) for the analysis of workers' mobility decisions. The ECHP is a panel of ex-ante homogenized individual data covering 15 countries from 1994 to 2001. Each household is interviewed once a year and every individual present in the initial sample is followed over the eight waves. Germany, Luxembourg and the U.K. quit the survey after three years⁶ whereas Austria, Finland and Sweden enter the panel in 1996 (1997 for Sweden).

Each observation consists of a rich set of individual characteristics, such as age and gender, together with standard information on the present job: wage, date of start... Two groups of variables are especially relevant to our analysis: the nature of job-to-job transitions, and satisfaction variables with various non-wage characteristics.

The definition of voluntary mobility: Since we want job-to-job transitions to reveal individual preferences over jobs, we restrict the definition of voluntary mobility to an unconstrained transition from one job to a "better" one. To this end we use a variable which presents the reason why the individual has stopped working in her previous job. The twelve possible answers to this question are reported in Table 1.

<< Table 1 about here >>

Every answer, except 2, 3 and 4, could be thought of as a voluntary quit since the worker has not been laid off. However we consider answers 5 to 12 (when job-to-job mobility is caused *e.g.* by a marriage or the birth of a child) as a sort of constrained mobility which may not reveal the individual's preferences over jobs. We thus define *voluntary mobility* as the transitions from one job to a "better or more suitable" one (answer 1), and *constrained mobility* for those who quit for any other reason (answers 2 to 12). We now look at the non-wage determinants of voluntary mobility.

Amenities: Among the numerous job characteristics available in the ECHP is a set of job amenities. The data we use gives the subjective valuation of the worker over a given aspect of her job. The typical question is:

How satisfied are you with your present job in terms of (amenity)?

and individuals use a scale from 1 ("*not satisfied at all*") to 6 ("*fully satisfied*") to indicate their degree of satisfaction. The question remains the same for the following job characteristics:

⁶In order to observe these three countries during the whole period 1994-2001, Eurostat has combined the ECHP with the GSOEP (Germany), the PSELL (Luxembourg) and the BHPS (U.K.). Unfortunately, non-wage characteristics are misreported when available in these national surveys.

- type of work (TYPEW)		- hours worked (WHOURS)
- working conditions/ environment (COND)		- distance to job/ commuting (DIST)
- working times (day/ night time etc...) (WTIME)		- job security (SECUR)

For the analysis to be clearer and the estimation to be more tractable, we will cluster the answers into two levels of satisfaction: an amenity equal to 1 (answers 5 and 6) will mean that individuals are actually satisfied and 0 (answers 1 to 4) that they are either unsatisfied or neutral. This rather arbitrary choice is made for convenience. It is consistent with the literature following Rosen (1986) where amenities take two values: zero for “bad” jobs, one for “good” jobs.⁷

Even though the ECHP is an ex-ante harmonized panel, some variables (especially amenities) may not be available in every wave and/ or country. Therefore we restrict our analysis to countries where all waves are available and amenities are rarely missing (the non-response rate is less than 1%). In this version of the paper, we focus on Denmark (DNK), France (FRA) and the Netherlands (NLD).

Individual Characteristics: We lastly present the individual characteristics we use in the subsequent analysis: “age” and “age²” are continuous variables; “sex” is a gender dummy, which equals 1 for women; “married” is a dummy indicating whether the individual is single (0) or not; and “kid” indicates if the individual has children under 12. Finally, “education” is a variable taking three values, from 1 (less than second stage of secondary education) to 3 (third level education).

2.2 Sample description

We merge every two consecutive waves of the ECHP and append the seven resulting tables in order to have a sample containing an *ex-ante* and an *ex-post* situation (respectively denoted as t and $t + 1$) for every individual/ year in the survey. More precisely, a worker present in the eight waves is associated with seven observations, each observation containing her job status (employment, wage⁸, amenity, etc...) and individual characteristics (age, marital status, etc...) both at date t and $t + 1$. Therefore an individual appears up to seven times in the data and for each observation she can experience one of the following transitions:

⁷It is common practice in the analysis of subjective data to estimate ordered models, such as ordered PROBIT (see Senick, 2003, and the references therein). Still these methods often involve the arbitrary clustering of some categories (typically the lowest levels of satisfaction). We also estimated our model for “good” amenities corresponding to levels 4, 5 and 6. The results remained qualitatively similar.

⁸We use *monthly* wages detrended on year dummies.

- stay employed in the same job		- make a job-to-unemployment transition
- stay unemployed		- make a voluntary job-to-job transition
- make an unemployment-to-job transition		- make a constrained job-to-job transition

Since we do not focus on labor participation, we cluster unemployment and inactivity. Moreover we define employment as paid jobs that last more than 15 hours per week.⁹ The precise construction of our samples (one per country) is presented in Appendix A.

Table 2 shows the main descriptive statistics on our samples. The first three rows present the number of individuals and the number of actual *ex-ante/ ex-post* observations. The next six rows give the proportions of each type of transition. We note that individuals tend to stay in their job, with an average probability of staying in the same job between two consecutive years equal to two thirds. This corresponds to an average job duration of three years. Interestingly, this duration is very similar in the three countries we study. Yet, there is some dispersion among countries in the probability of making a job-to-job transition, which ranges between four and ten percents of total transitions. In particular, voluntary job-to-job mobility is significantly more frequent in Denmark (4.2%) than in France (1.7%). In all cases, though, these amount to a small proportion of transitions on the labor market.

<< **Table 2 about here** >>

The last two rows of Table 2 are important motivations for our analysis. Indeed we can see that most voluntary job changes are associated with a wage gain whereas job stayers and constrained job movers more frequently experience a wage cut. This suggests that the wage influences job change decisions. Yet, the proportion of wage increases ranges from only 60% (in France) to 73% (in the Netherlands) of *voluntary* job-to-job transitions. Up to a third of voluntary job movers experience a wage cut even if the new job is said to be “better or more suitable” than the previous one. If at least part of these transitions with wage cuts are not spuriously generated by measurement error, these statistics show that the wage is not the only characteristic workers value, and we should look at other job characteristics to explain voluntary mobility.¹⁰

To investigate further this issue, we compute in Tables 3a-3c the transition matrices for each country/ amenity conditional on voluntary, constrained or within-job

⁹Self-employed people are likely to differ from other workers in many ways. In particular, lower risk aversion can cause much different career profiles. In this paper we assume away this issue, and drop the self-employed from our samples.

¹⁰Changes in hours worked provide a possible explanation for voluntary quits associated with wage cuts. However, less than 10% of these transitions correspond to changes from full-time (defined as more than 30 hours per week) to part-time work in the three countries we consider.

transitions.¹¹

<< **Tables 3a-3c about here** >>

As every off-diagonals show (with rare exceptions such as “distance to job” in Denmark and the Netherlands), the transition matrices in Table 3a are all non symmetric: voluntary job changers are more prone to gain than to lose amenities. This is particularly true for two amenities: “type of work” and “working conditions”. On the contrary, transition matrices are strikingly symmetric when looking at job stayers (Table 3c). In constrained transitions (Table 3b), non-wage characteristics are improved in terms of satisfaction, yet less so than in voluntary ones. Thus, the increase in satisfaction with non-wage characteristics seems to be specific to voluntary mobility.

These few descriptive statistics tend to confirm the idea that the wage is not the only determinant of workers’ voluntary mobility and that non-wage characteristics are likely to enter job valuation. We now proceed to a formal test of this intuition.

3 A model of wages, amenities, and job-to-job mobility

In this section, we introduce a framework to study job-to-job mobility. We first present our modeling of job-to-job mobility, based on generalized reservation wages. We then incorporate these structural reservation wages into a selection model of job mobility with two outcomes: wages and amenities.

3.1 A parsimonious modeling of job mobility decisions

We assume in the following that the non-wage dimension(s) of a job can be clustered in a possibly multivariate index a called its *amenity*. We denote the wage as y . Thus, a job is characterized by a pair (y, a) of wage/amenity. We consider the following problem: let a given individual be employed in a job (y_1, a_1) and suppose she is offered (y_2, a_2) . Will she make the job-to-job transition or stay in her present job ?

Under some rather weak monotonicity and regularity assumptions on the job mobility decision process, we show in Appendix B that there exists a set of reservation wages $\tau_{a_1 a_2}(y_1)$ conditional on the current job characteristics and on the offered amenity level a_2 such that the individual will actually move if and only if:

$$y_2 \geq \tau_{a_1 a_2}(y_1).$$

To illustrate our representation of mobility decisions, assume that there are two types of job, “good” ($a = 1$) and “bad” ($a = 0$). Then Figure 1 shows that the

¹¹In Table 3, $\mathbb{P}(a_1, a_2)$ is the joint probability law of (a_1, a_2) . It is computed as the ratio of the number of voluntary (resp. constrained or within-job) transitions from amenity $a_1 = 0, 1$ to amenity $a_2 = 0, 1$, divided by the number of all voluntary (resp. constrained or within-job) transitions.

individual featured in the “bad” job ($a_1 = 0$) with wage y_1 accepts every offer either of a bad job ($a_2 = 0$) paid more than $\tau_{00}(y_1)$, or of a good job ($a_2 = 1$) with a wage higher than $\tau_{01}(y_1)$. In the case of “good” and “bad” jobs, we intuitively expect $\tau_{01}(y_1) < \tau_{00}(y_1)$, for all y_1 .

This modeling allows to define two different Marginal Willingnesses to Pay for amenity a . The MWP for a at the *current* job is defined as:¹²

$$MWP = \frac{\partial \tau_{a_1 a_2}(y_1)}{\partial a_1} / \frac{\partial \tau_{a_1 a_2}(y_1)}{\partial y_1}.$$

The Marginal Willingness to Pay for amenity *offers* is:

$$MWP^* = -\frac{\partial \tau_{a_1 a_2}(y_1)}{\partial a_2}.$$

In this framework, wage/amenity compensation means that the reservation wage of an individual employed at (y_1, a_1) and offered amenity a_2 is increasing in a_1 and decreasing in a_2 :

$$\text{Compensation} \Leftrightarrow MWP > 0 \quad \text{and} \quad MWP^* > 0.$$

This compact representation mixes two important determinants of mobility decisions: preferences and transition costs. To understand the generality of our modeling, first assume that no cost is associated to job mobility. Suppose further that individual preferences can be represented by a concave utility function $U(y, a)$. An individual moves from one job to another if the utility of the second job is higher than the utility of the first one. In other words there is an indifference curve passing through (y_1, a_1) and $(\tau_{a_1 a_2}(y_1), a_2)$ and the reservation wage solves:

$$U(\tau_{a_1 a_2}(y_1), a_2) = U(y_1, a_1).$$

In this case, $\tau_{a_1 a_2}(y_1)$ is the monetary compensation the individual requires to move to a a_2 job. Assume again that a can take two values, 0 (“bad”) or 1 (“good”). Assume also that $\tau_{a_1 a_2}(y_1) = y_1 + \tau_{a_1 a_2}$. In the terminology of Rosen (1974, 1986), $\tau_{10} = -\tau_{01}$ is the hedonic price of a . Moreover, in this case the two Marginal Willingnesses to Pay defined above are identical, and equal to the marginal rate of substitution $\frac{\partial U}{\partial a} / \frac{\partial U}{\partial y}$.

Now, suppose that transition costs are not negligible. Then the “sale” (τ_{10} in the previous example) and the “purchase” ($-\tau_{01}$) hedonic prices of a are no longer necessarily equal. Figure 1 illustrates how transition costs can induce non-symmetric mobility decisions. A worker at $(y_1, 0)$ offered $(\tau_{01}(y_1), 1)$ decides to change job. Still, a subsequent offer of $(y_1, 0)$ is not enough to compensate the worker, as job mobility is associated with costs. In other words, there is generally no indifference curve passing through $(y_1, 0)$, $(\tau_{01}(y_1), 1)$, and $((\tau_{10} \circ \tau_{01})(y_1), 0)$. Our representation therefore

¹²We implicitly assume here that a is a continuous scalar and τ is differentiable with respect to its different arguments.

extends Rosen’s (1986) modeling of labor supply to job-to-job mobility, where one would expect transition costs to be significant.¹³

We now turn to the construction and estimation of a model of transitions on the labor market, where voluntary mobility is ruled by the above reservation wages, i.e. the τ functions.

3.2 The model

We here model wage, amenity and mobility processes of employed workers.¹⁴ For ease of exposition, we assume that all job-to-job transitions are voluntary. In the empirical analysis, we actually allow for constrained transitions. See Appendix C for a detailed presentation.

We assume that every job in the market consists in a wage y , a real-valued non-wage amenity a , and two unobserved job characteristics $\theta = (\theta_1, \theta_2)$. θ_1 and θ_2 are the “objective” and “subjective” quality of the worker/ firm match, respectively. They are supposed constant within job. Lastly, x denotes observed individual characteristics, which can be time-varying or not.¹⁵

Wage/ amenity equations: Let $i \in \{1 \dots N\}$ be an individual employed at period t with characteristics x_{it} . Her present job consists in the wage/ amenity pair (y_{it}, a_{it}) , together with the quality of the match θ_{it} . We assume that she can choose between two alternatives:

- **Within-job:** If the worker chooses to remain in the same job at $t + 1$, then she receives (y_{it+1}^r, a_{it+1}^r) , where the wage/ amenity are given by:

$$y_{it+1}^r = x'_{it+1} \alpha_y^r + \theta_{1it+1} + u_{yit+1}^r, \quad (1)$$

$$a_{it+1}^r = \mathbf{1} \{ x'_{it+1} \alpha_a^r + \beta_{1a}^r \theta_{1it+1} + \theta_{2it+1} + u_{ait+1}^r > 0 \}. \quad (2)$$

The quality of the worker/ firm match does not vary within job, so that:

$$\theta_{1it+1} = \theta_{1it}, \quad (3)$$

$$\theta_{2it+1} = \theta_{2it}. \quad (4)$$

In equation (1), the wage is assumed to depend on observed individual characteristics (x_{it+1}), the unobserved match quality ($\theta_{1it+1} = \theta_{1it}$), and random shocks (u_{yit+1}^r).

The amenity in the job depends on θ_{1it} , as well as on the “subjective” unobserved characteristic θ_{2it} . It is convenient to think of equation (2) as a reduced form. The

¹³The τ modeling also generalizes Altonji and Paxson (1988), who model individual preferences for wages and hours worked and allow for fixed costs. In our framework, costs are assumed to satisfy property 1 (see Appendix B). Namely, the marginal utility of a (y, a) job with respect to the wage is assumed higher than the marginal cost of this job, again with respect to the wage. This is a rather weak assumption, which nests fixed costs as soon as the wage enters positively the utility function.

¹⁴The focus of the paper is on job-to-job mobility, and wage/ amenity correlation for employed workers. In a preliminary version of the paper, we incorporated unemployment as a specific state with little influence on the results.

¹⁵In the rest of the paper, we will not distinguish a random variable from its realization. The meaning will be clear from the context.

“objective” characteristics of a given job (y_{it}, \tilde{a}_{it}) are supposed to depend on common characteristics: fixed (θ_{1it}) and time-varying (x_{it}) . Then workers evaluate the non-monetary job aspect in terms of satisfaction. We model this by introducing a subjective threshold s_{it} such that $a_{it} = \mathbf{1}\{\tilde{a}_{it} > s_{it}\}$. We assume that this threshold depends on x_{it} , θ_{1it} and on the second (“subjective”) component of the quality of the worker/ firm match θ_{2it} . It is then clear that the reduced form (2) mixes the “objective” amenity and the “subjective” interpretation of the amenity in terms of satisfaction.¹⁶ The amenity evolves randomly around its mean value in the job, which is a mix of objective and subjective determinants.

• **Between-job:** If the worker changes to another job, then she has accepted an offer drawn from (y_{it+1}^*, a_{it+1}^*) , where:

$$y_{it+1}^* = x_{it}^* \alpha_y + \beta_y^* \theta_{1it} + u_{yit}^*, \quad (5)$$

$$a_{it+1}^* = \mathbf{1}\{x_{it}^* \alpha_a + \beta_{1a}^* \theta_{1it} + \beta_{2a}^* \theta_{2it} + u_{ait}^* > 0\}. \quad (6)$$

Job offers depend on the determinants of the mean wage and amenity in the current job. Together, x_{it} and θ_{it} define groups of workers who face the same distribution of job offers, independently of the particular wage/ amenity realizations.

Then, after the worker has started to work in her new job, the quality of the match is formed. We assume that the quality of the match between the worker and the new firm is correlated with the starting wage/ amenity values in the job by:

$$\theta_{1it+1} = x_{it+1}' \alpha_{\theta_1} + \gamma_{\theta_1} y_{it+1} + u_{yit+1}, \quad (7)$$

$$\theta_{2it+1} = x_{it+1}' \alpha_{\theta_2} + \beta_{\theta_2} \theta_{1it+1} + \delta_{\theta_2} a_{it+1} + u_{ait+1}. \quad (8)$$

Equations (7) and (8) define the law of motion of wage/ amenity unobserved determinants. Empirically, we find that the correlation between the first wage/ amenity in a job and the quality of the match θ is positive and large. Thus, θ_{it+1} is significantly correlated to θ_{it} , through (5) and (6).

Job mobility decisions: Let z_{it} denote the variable indicating whether the individual i has changed job voluntarily between t and $t + 1$. The decision variable z_{it} is assumed to follow a reservation wage rule similar to the one introduced in the last subsection. Namely, an individual employed at a job with characteristics (y_{it}, a_{it}) and offered (y_{it+1}^*, a_{it+1}^*) accepts this offer and changes job if: $y_{it+1}^* > \tau_{a_{it} a_{it+1}^*}(y_{it}; x_{it})$.

We model the reservation wage as:

$$\tau_{a_{it} a_{it+1}^*}(y_{it}; x_{it}) = x_{it}' \alpha_z + \gamma_z y_{it} + \delta_z a_{it} + \delta_z^* a_{it+1}^* + u_{zit}. \quad (9)$$

Our representation of job mobility decisions thus writes:

$$z_{it} = \mathbf{1}\{y_{it+1}^* > x_{it}' \alpha_z + \gamma_z y_{it} + \delta_z a_{it} + \delta_z^* a_{it+1}^* + u_{zit}\}, \quad (10)$$

¹⁶It is also clear that this “subjective” interpretation involves two rather different dimensions. Individuals can give different answers because they have distinct preferences for the amenity. They can also have different judgements about the 1–6 ranking proposed. For instance, some workers will never answer that they are “fully satisfied” with the amenity (answer 6), *ceteris paribus*. Our model does not disentangle these two dimensions.

and the outcomes are as follows:

$$(y_{it+1}, a_{t+1}) = (y_{it+1}^*, a_{t+1}^*) \text{ if } z_{it} = 1, \quad (11)$$

$$= (y_{it+1}^r, a_{t+1}^r) \text{ if } z_{it} = 0. \quad (12)$$

The model composed of equations (5)-(6) and (10)-(11) is a censored regression model with endogeneous threshold. We shall refer to this part of the model as the *selection model*.

Initial period: Let $[T_{i0}, T_{i1}]$ be the observation length for individual i . To consistently estimate the unobserved heterogeneity distributions of θ_{1i} and θ_{2i} , we model the conditional density of $(\theta_{1T_{i0}}, \theta_{2T_{i0}})$ for the first observation, for which we have no information on past mobility, by:

$$\theta_{1iT_{i0}} = x'_{iT_{i0}} \alpha_{\theta_1}^{init} + \gamma_{\theta_1}^{init} y_{iT_{i0}} + u_{yiT_{i0}}^{init}, \quad (13)$$

$$\theta_{2iT_{i0}} = x'_{iT_{i0}} \alpha_{\theta_2}^{init} + \beta_{\theta_2}^{init} \theta_{1iT_{i0}} + \delta_{\theta_2}^{init} a_{iT_{i0}} + u_{aiT_{i0}}^{init}. \quad (14)$$

These equations follow the same pattern as (7) and (8).

3.3 Assumptions and comments

Reservation wages: Our specification of the reservation wage (9) has several important implications. As τ is a function of the wage and amenity values at t and $t+1$, it is implicitly assumed in (9) that workers' expectations are *myopic*. Arguably, as pointed out by Postel-Vinay and Robin (2002) and Connolly and Gottschalk (2002), wage *growth* expectations can enter job mobility decisions. For instance, workers' mobility can be explained by a lower initial wage and a steeper wage path. Our modeling does not capture this behavior. Instead, in our model voluntary transitions with wage cuts are explained by (better) amenities. Empirically, both mechanisms are likely to play a part, motivating the construction of a model including amenities and dynamic expectations. In our framework, it is theoretically possible to include *e.g.* future match qualities $\theta_{it'}$, $t' > t$, in the reservation wage. However, the estimation of such a model rises computational difficulties that we could not solve. We hence focus on the role of non-wage characteristics in mobility decisions and see our analysis as an alternative to Postel-Vinay and Robin (2002) and Connolly and Gottschalk (2002).

Next, apart from the characteristics of the current job, the reservation wage also depends on individual characteristics (x_{it}), an example of which is age. These characteristics can thus have two distinct effects on job mobility decisions, direct, and indirect (through job offers). Lastly, the reservation wage is stochastic conditionally on observed characteristics, which we capture by the random shocks u_{zit} . Although many models of transitions assume deterministic reservation wages (see *e.g.* Flinn and Heckman, 1982), we shall see in sections 5 and 6 that, in the context of job-to-job mobility, it is important to allow for variability in τ .

From (9) we can compute the two different Marginal Willingnesses to Pay defined in 3.1. We define δ_z/γ_z to be the MWP for the amenity at the *current* job, and $-\delta_z^*$ to be the MWP for the amenity in job *offers*. We expect the wage at the current job to increase the reservation wage, *i.e.* $\gamma_z > 0$. In this case, wage/ amenity compensation reads: $\delta_z > 0$ (current job’s characteristics), and $\delta_z^* < 0$ (job offers).

Assumptions on the shocks: All the residuals in (1) to (14) are assumed *i.i.d.* with zero mean, and independent of covariates. We allow for cross-sectional correlation between the residuals of all wage and amenity equations.

Let “ \perp ” and “ $\perp \mid$ ”, respectively, mean unconditional and conditional statistical independence. We further assume that:

$$u_{zit} \perp (u_{yit}^*, u_{ait}^*), \quad (15)$$

$$(u_{zit}, u_{yit}^*, u_{ait}^*) \perp (u_{yit+1}^r, u_{ait+1}^r). \quad (16)$$

Exclusion restriction: As an important implication of the assumptions on (u_{yit}^*, u_{ait}^*) , the following conditional independence condition holds:

$$(y_{it+1}^*, a_{it+1}^*) \perp (y_{it}, a_{it}) \mid (x_{it}, \theta_{1it}, \theta_{2it}). \quad (17)$$

Our identification strategy relies strongly on this exclusion restriction. In the model, θ and x define groups of workers who are homogeneous with respect to the job offers they receive. We think of this assumption as consistent with a “social” interpretation of the hiring process. As targeting job offers to a specific individual is costly to firms, some “grouping” of job offers can be rational on the demand side. Then, if job offers are grouped in terms of characteristics θ and x , particular realizations of the wage/ amenity values y_{it} and a_{it} can be used to separately identify workers’ job change decisions and job offers.

Our method thus relies on exclusion restriction (17), conditional on unobserved variables identified from the Panel. In a different context, Carneiro, Hansen and Heckman (2002) use a similar insight to impose the independence assumptions commonly invoked in the matching literature. In the next section, we show that these conditions are sufficient for the model parameters to be identified, and explain our estimation method.

4 Identification and estimation issues

In this section, we address the identification and estimation of model (1)-(14). There are two potential identification problems: the censored regression model of job-to-job mobility, and the unobserved heterogeneity distributions.

4.1 Selection

Identification of the censored regression model To achieve the identification of the selection model given by (5)-(6) and (10)-(11), we use exclusion restriction (17).

Consider the censored regression model given by (5)-(6) and (10)-(11). Denote as f_y the distribution function of the random variable y , which can be continuous or discrete, with respect to the appropriate measure. Similarly, denote as $f_{y|z}$ the conditional distribution function of y given z . When the conditioning is obvious, we shall simply write f_y .

Suppose that the distribution function of $\theta_{it} = (\theta_{1it}, \theta_{2it})$ is identified from the data. Then the sampling process identifies:

$$\underbrace{f_{z,y,a}(z_t = 1, y_{t+1}, a_{t+1} | y_t, a_t, \theta_t)}_{\text{data}} = \underbrace{f_{z|y^*,a^*}(z_t = 1 | y_{t+1}, a_{t+1}, y_t, a_t, \theta_t)}_{\substack{\text{mobility} \\ \text{decision}}} \times \underbrace{f_{y^*,a^*}(y_{t+1}, a_{t+1} | y_t, a_t, \theta_t)}_{\text{offers}}, \quad (18)$$

where we dropped the subscripts i and the implicit conditioning on x_{it} for expositional convenience.

The Left Hand Side in (18) is known, and could be estimated by standard nonparametric regression methods. It is yet clear from (18) that the distributions of interest, namely the mobility decision and the offer functions, are not identified separately without further assumptions.

Noticeably, exclusion restriction (17) is sufficient for (semi-parametric) identification to hold. To see why, note that, since y_t is continuous, (17) allows to identify the log-derivative of the mobility decision term in (18). Let G_t be the CDF of u_{zt} . From (18) and assumption (15) the following equality holds:

$$\frac{\partial}{\partial y_t} \ln f_{z,y,a}(z_t = 1, y_{t+1}, a_{t+1} | y_t, a_t, \theta) = -\gamma_1 \frac{G'_t}{G_t}(y_{t+1} - \gamma_z y_t - x'_t \alpha_z - \delta_z a_t - \delta_z^* a_{t+1}), \quad (19)$$

where $G'_t(\cdot)$ is the derivative of the univariate function G_t .

The RHS in (19) is thus identified from the data. Moreover, (19) is formally analogous to a single-index model. From this analogy, we deduce that under the assumptions stated in Manski (1988) the parameters of the mobility decision are identified, together with the function $\frac{G'_t}{G_t}$.¹⁷ G_t is thus identified up to a multiplicative constant. Using (18) and integrating over (y_{t+1}^*, a_{t+1}^*) eventually identifies this constant.

Estimation: maximum likelihood We assume that all the residuals in the model follow normal distributions. Moreover, (u_{yt}^*, u_{at}^*) and (u_{yt}^r, u_{at}^r) are assumed binormal

¹⁷Note that the last of Manski's (1988) *maintained assumptions* requires that G'_t/G_t be strictly increasing on the real line. Notice that G'_t/G_t is the inverse Mill's ratio of ϵ_t . For a large class of distributions, such as the normal, it is strictly *decreasing* on the real line. It is straightforward to check that Manski's proof does not require that G'_t/G_t be a CDF, and applies to this case as well.

with zero means and covariance matrices:

$$\begin{pmatrix} (\sigma_y^*)^2 & \rho_{ya}^* \sigma_y^* \\ \rho_{ya}^* \sigma_y^* & 1 \end{pmatrix} \quad \text{and} \quad \begin{pmatrix} (\sigma_y^r)^2 & \rho_{ya}^r \sigma_y^r \\ \rho_{ya}^r \sigma_y^r & 1 \end{pmatrix},$$

respectively. Note that the standard deviation of u_{zt} , σ_z , is identified from the selection model and needs not equal one.

Equations (5)-(6) and (10)-(11) form a censored regression model with endogenous threshold. In our setting, where outcomes are both discrete (amenities) and continuous (wages), we cannot apply standard two-step methods (Heckman, 1976, and Maddala, 1983). We thus use Maximum Likelihood for estimation. However, initial conditions have to be properly chosen. Indeed, the likelihood of the selection model is not globally concave and numerical convergence of the Newton algorithm is often difficult to obtain (see Nelson, 1977, for a comparable problem). Appendix D details the mathematical expression of the likelihood, and the method we use to find initial conditions.

4.2 Unobserved heterogeneity

In the previous discussion, θ_{1it} and θ_{2it} were assumed to have known distributions. We here show that the latter are indeed identified, under standard assumptions in panel data and dynamic binary choice models. We then expose our estimation method.

Identification of the match quality: The developments in this paragraph are restricted to within-job wage and amenity changes. We thus suppress the t subscripts in θ_{1it} and θ_{2it} for ease of notation.

For the sake of flexibility, we model (θ_1, θ_2) as random variables. A sufficient source of identification of unobserved heterogeneity θ_1 comes from the repetition of wage measures within jobs.

The within-jobs wage equations are given by:

$$\tilde{y}_{it}^r = \theta_{1i} + u_{yit}^r, \quad (20)$$

where $\tilde{y}_{it}^r \equiv y_{it}^r - x_{it}' \alpha_y^r$, and u_{yit}^r is *i.i.d.* and independent of x_t and θ_1 .

It is known at least since Kotlarski (1967) that two observations t and t' are sufficient for the distributions of θ_1 , u_{yit}^r and $u_{yt'}^r$ to be nonparametrically identified in (20) in the case where u_{yit}^r and $u_{yt'}^r$ are independent. Since workers stay on average more than three years in a given job, this condition is easily fulfilled in our data. Lastly, note that, since $\mathbb{E}(y_{it}^r | x_{it}) = x_{it}' \alpha_y^r$, α_y^r is trivially identified in (1).

It now remains to be shown that θ_2 is identified in:

$$a_{it}^r = \mathbf{1} \{x_{it}' \alpha_a^r + \beta_{1a}^r \theta_{1i} + \theta_{2i} + u_{ait}^r > 0\},$$

where u_{ait}^r is *i.i.d.* and independent of x_t , θ_1 and θ_2 , provided that we dispose of more than two dates.

To show the semi-parametric identification of (2), assume that we dispose of two dates of observation, $t = 1, 2$. Manski (1988) shows that for $(\alpha_a^r, \beta_{1a}^r)$ to be identified, one of the regressors has to be continuously distributed with non-vanishing density. Let $v_t = \theta_2 + u_{at}^r$. Under conditions X1 and X3 of Manski (1988), the parameters are identified (up to scale) together with the marginal distributions of v_t , $t = 1, 2$. To identify the distributions of interest separately, one needs to identify the joint density of (v_1, v_2) . For this purpose, we also assume that (x_1, x_2) has large support. Namely:

$$Supp(v_1, v_2) \subset Supp(x_1' \alpha_a^r + \beta_{1a}^r \theta_1, x_2' \alpha_a^r + \beta_{1a}^r \theta_1). \quad (21)$$

Under assumption (21), the distribution of (v_1, v_2) is identified. Kotlarski's theorem thus applies, and the distributions of θ_2 , u_{a1}^r and u_{a2}^r are also identified.

Estimation: the EM algorithm We here explain how we estimate the unobserved heterogeneity distributions. The details of the procedure are given in Appendix D. Following Heckman and Singer (1984), we model the unobserved distributions θ_1 and θ_2 as discrete. Let N denote the number of individuals in the sample. We assume that there exist two integers K_1 and K_2 , a mapping:

$$\begin{aligned} \{1 \dots N\} &\rightarrow \{1 \dots K_1\} \times \{1 \dots K_2\} \\ i &\mapsto (k_{1i}, k_{2i}), \end{aligned}$$

and parameters $(\vartheta_{11}, \dots, \vartheta_{1K_1}), (\vartheta_{21}, \dots, \vartheta_{2K_2})$ such that $(\theta_{1i}, \theta_{2i}) = (\vartheta_{1k_{1i}}, \vartheta_{2k_{2i}})$.

In our parametric setting, we use the EM algorithm of Dempster, Laird and Rubin (1977) to estimate the parameters of the model, together with the two discrete distributions. This amounts to treating k_{1i} and k_{2i} as random variables. Starting with initial guesses for the parameters, one computes, in the expectation (E) step, the posterior probabilities that $(k_{1i}, k_{2i}) = (k_1, k_2)$ given the data, for all k_j in $\{1, \dots, K_j\}$, $j = 1, 2$ and for all individuals. Then in the maximization (M) step one maximizes the likelihood of the observations, weighted by the posterior probabilities.

As for the choice of K_1 and K_2 there is a trade-off between the accuracy of the description of the unobserved heterogeneity distributions and the tractability of the estimation due to the small number of voluntary job-to-job transitions. We found $K_1 = 4$ and $K_2 = 2$ to be a convenient choice for the three countries we study. Allowing for more heterogeneity does not modify parameter estimates substantially. However when $K_1 < 4$ and/ or $K_2 < 2$, local maxima can appear in the likelihood and modify the diagnosis on workers' mobility (even though the estimates still show wage/ amenity compensation). We discuss this issue in Appendix E.

The estimation of the global model takes the form of simple steps. In the M-stage of the algorithm, the equations ruling all transitions but voluntary job-to-job mobility (5)-(6) and (10)-(11) (see Appendix C for details) are estimated either by PROBIT or by OLS, weighted by the posterior probabilities. Appendix D shows how

we incorporate the likelihood of the censored regression model into the estimation of the global model *via* the EM algorithm.

5 Estimation results

In this section, we first present our results for the discrete distributions of unobserved heterogeneity. We then comment on the parameter estimates of the censored regression model, and weight the influence of the different factors on mobility decisions.

5.1 “Productive” and “subjective” heterogeneity

Wage and amenity regressions: The global model (see Appendix C) features many parameters which are difficult to comment on. For ease of exposition, we first present in Table 4 the results of two regressions: OLS of wage (column 1) and PROBIT of the amenity (2). These regressions are conditional on some observed characteristics, and on the dummies of the “productive” and “subjective” quality of worker/ firm matches.¹⁸

<< Table 4 about here >>

Table 4 presents the results of these regressions for Denmark, with the amenity “type of work”. The results for other countries/amenities are qualitatively similar. First, note that the effects of observed characteristics are as expected. The wage is concave in age, and negatively correlated with being a woman. The gender effect holds also for the satisfaction variable, as women are on average less satisfied with their “type of work”. The satisfaction variable is convex in age, as often found in the literature on qualitative data (see *e.g.* Clark and Oswald, 1994). Lastly, “married” and “kid” have mostly insignificant effects on the wage and the amenity.

Next, column 2 shows that the wage distribution is well approximated by the four groups of discrete unobserved heterogeneity, with a R -squared of .77. When we estimate the same wage regression without the group dummies (first column), the R -squared falls significantly, to .23. We also estimated the model with 2 and 3 groups of “productive” heterogeneity. Two groups increased significantly the fit, with a R -squared of .56, and three groups gave a R -squared of .67.

Lastly, the inclusion of the group dummy θ_2 in the amenity regression (column 5) increases the R -squared, from .01 to .29.¹⁹ Thus, it seems necessary to account for unobserved heterogeneity to describe amenity distributions, while observed heterogeneity accounts for a large part of the wage variance. Moreover, as columns 3

¹⁸To perform these regressions, we duplicated the sample $K_1 K_2$ times, and weighted each subsample by the corresponding posterior probabilities computed in the last M-step of the EM algorithm before convergence was achieved.

¹⁹We define the “ R -squared”, for a PROBIT regression $z = \mathbf{1}_{x'\alpha+u>0}$ with $\mathbb{V}(u) = 1$ as:

$$R^2 \equiv \frac{\mathbb{V}(x'\hat{\alpha})}{1 + \mathbb{V}(x'\hat{\alpha})},$$

which is invariant with respect to normalization.

and 4 show, “productive” unobserved heterogeneity (θ_1) has very little explanatory power on the satisfaction variable. Thus the determinants of the wage and amenity distributions appear almost orthogonal.

Observed and unobserved heterogeneity: We confirm this finding in Table 5, which presents the correlation between unobserved heterogeneity and the gender and education dummies. Higher θ_1 appears positively correlated with higher education and being a male, two key variables in wage regressions. Interestingly, θ_2 is almost randomly distributed among these observed characteristics, with a probability of being satisfied with one’s “type of work” equal to two thirds, irrespective of one’s sex or education degree.

<< **Table 5 about here** >>

Wages, amenities and job mobility: Tables 4 and 5 show that the amenity variables are almost orthogonal to the determinants of the wage (x and θ_1). Now, one could think that these satisfaction variables are randomly distributed in the population. In that case, they would have no economic meaning.

To address this issue, we present in Table 6 the estimates of a PROBIT regression of the voluntary mobility variable z_{it} on individual and current job’s characteristics (x_{it}, y_{it}, a_{it}), and unobserved dummies ($\theta_{1it}, \theta_{2it}$), for workers who either stayed in their job or changed job voluntarily between two consecutive dates.

<< **Table 6 about here** >>

Note, as before, that the effects of observed characteristics are as expected: being older (on average) and being a woman significantly reduce the quit probability. “married” and “kid” have also negative effects, though insignificant.

Next, the PROBIT in column one features a negative and statistically significant coefficient for the current satisfaction with “type of work”. If the inclusion of θ_1 does not modify the coefficient of current satisfaction a_t , adding heterogeneity θ_2 does increase the (negative) effect of current satisfaction on mobility, from $-.28$ to $-.48$, where both estimates are highly significant. Allowing for specific unobserved heterogeneity θ_2 thus corrects for the endogeneity of a_t , and reinforces the negative effect of current satisfaction on the quit probability. Similar results hold for the other countries and the other amenity variables. Therefore, although non-wage amenities are weakly correlated with observed individual characteristics, they seem economically relevant as they affect mobility decisions.

We lastly turn to the effect of the current wage on the mobility decision. Comparing the first two columns in Table 6 shows that y_t is also endogenous in the PROBIT regression without unobserved heterogeneity. Inclusion of θ_1 changes drastically the coefficient of y_t from a positive and significant value of $.19$ to a negative and significant value of $-.52$. Allowing for θ_1 turns the current wage into a strong predictor

of voluntary *im*-mobility. Moreover, this effect is stronger, the more precisely heterogeneity is modeled. With two groups, the coefficient of y_t is already negative, but insignificant at conventional levels ($-.07$, with a standard error of $.09$). When a third group is allowed for, it becomes significantly negative ($-.23$, with a standard error of $.10$).

The last column in Table 6 thus suggests that satisfaction with one’s job, either in the form of the wage or of other aspects of the job, strongly deters workers from quitting. This effect had already been noticed in several papers, *e.g.* Clark and Oswald (1994). It is also the main result of Gronberg and Reed’s (1994) analysis. Table 6 makes it clear that the negative impact of current satisfaction on job change decisions is stronger when unobserved heterogeneity is allowed for. According to the model introduced in 3.2 this comes from the heterogeneity of the job offers drawn by workers. The second part of this section deals with the analysis of the parameter estimates of this global model.

5.2 Job offers and reservation wages estimates

Parameter estimates, job offers: Estimates of the parameters ruling wage/amenity offers and mobility decisions are displayed in Tables 7a-7c. We first note that wage offer estimates are almost invariant with respect to the amenity choice. Both age and unobserved heterogeneity θ_1 always seem to play an important role in their determination. Moreover, these effects are qualitatively the same as in cross-section, as illustrated by the comparison with Table 4. In particular, a higher unobserved “productive” heterogeneity is associated with higher wage *offers*, as it was shown above to be associated with higher wages in cross-section.

<< **Tables 7a-7c about here** >>

On the other hand, the estimates of the determinants of amenity offers are hardly significant. As in cross-section, again, the “subjective” heterogeneity θ_2 is the *only* variable that remains significant in every country/amenity. Moreover, this effect is the same as in cross-section: higher θ_2 means higher satisfaction with the amenity. The correlation between wage and amenity offers through the observed and unobserved regressors in the model, such as age or θ_1 , thus appears to be weak, or, as far as θ_1 is concerned, ambiguously signed.

Therefore, if there is wage/amenity correlation in job offers, it must come from correlation between the shocks u_y^* and u_a^* . Tables 7a-7c also feature the correlation of wage/amenity offers ρ_{ya}^* . This correlation could be high, as the recent theoretical results in Hwang *et al.* (1998) and Lang and Majumdar (2004) predict that firms’ competition to attract workers can lead to positive correlation in job offers in the presence of informational frictions. As Tables 7a-7c show, no clear conclusion arises from the signs of the estimates of ρ_{ya}^* . Correlation in job offers is negative in Denmark for the amenities “working hours”, “working times” and “job security”, but positive

in the Netherlands for the amenity “type of work”. In most cases the estimates are statistically insignificant. We also estimated the model by imposing $\rho_{ya}^* = 0$, with little influence on the other parameter estimates.

Parameter estimates, job mobility: We now turn to the mobility decision.²⁰ When significant, the age and/or age² parameters are positive. Age thus reduces significantly the probability of job change. This effect has been already noted in the literature, see *e.g.* Groot and Verbeke (1997). Being a woman is also associated with lower propensity to change job. Again, this result is consistent with the literature (as Xenogiani, 2003).

Unlike age and gender, the other observed characteristics do not seem to play a significant role in deciding whether to move or not. In the Netherlands and France, being married significantly reduces the propensity to change job, while the presence of kids has no effect. In Denmark, the two variables have a negative effect on the job change probability, but both coefficients are not significant at conventional levels.

We also included education as a regressor in the mobility equation. The results are not shown in this version of the paper and are available from the authors upon request. We found that more educated workers tend to have significantly lower reservation wages on average in Denmark. In the Netherlands the effect of education on the reservation wage is positive and significant. Yet, the introduction of education in the model had virtually no effect on the other parameter estimates.

Lastly, the estimates of the standard deviation σ_z range between .8 in Denmark and 2.4 in France. When comparing these figures to the standard deviation estimates of wage offers, we find a ratio between 5 (Denmark) and 9 (France). The quantity $\frac{(\sigma_y^*)^2}{\sigma_z^2 + (\sigma_y^*)^2}$ can be interpreted as the explanatory power of wage offers in the mobility decision. Our empirical estimates suggest that many other factors than wage offers influence the decision to quit. Moreover, this quantity is strikingly constant across amenities, suggesting that non-wage characteristics do not account for the main part of the heterogeneity in mobility behavior.

Such a low explanatory power of the wage and amenities in the quit decision is one of our main findings. To test the robustness of this result, we study in Appendix E three reasons why the σ_z estimates reported in Tables 7a-7c could be severely overestimated. The first reason is related to the non-concavity of the likelihood of the selection model. In many configurations, there are two local maxima, one of which corresponding to a significantly lower σ_z . In Appendix E, we show in an informal manner that this maximum is likely to be essentially driven by functional forms assumptions (*i.e.* normality). When unobserved heterogeneity is modeled in a flexible way ($K_1 \geq 4$, $K_2 \geq 2$), the parameter set corresponding to a large σ_z , as reported in Tables 7a-7c, is the global maximum of the likelihood.

Second, the dependence of voluntary mobility on age and gender could be very

²⁰In the following comments, a positive point estimate implies a rise in the reservation wage hence a *negative* effect on mobility.

nonlinear, which would bias the estimates of σ_z . In the second part of Appendix E, we separately estimate the model for men, women, and workers aged less or more than 35. The results in the various samples are strikingly similar, suggesting that the high σ_z estimates obtained are not driven by (non)linearities in age and gender.

Lastly, we address the issue of measurement error. We find that adding a 20% perturbation to the wage data does not modify substantially the parameter estimates of the reservation wage, except σ_z which becomes almost twice as large as the estimates reported in Tables 7a-7c. This suggests that our estimates of the heterogeneity in mobility decisions are likely to capture a lot of measurement error (which also affects the amenity and mobility variables). On the other hand, the parameters ruling wage/amenity compensation are unlikely to be severely affected by data failures.

To summarize the results of this paragraph, we find that mobility behaviors are indeed very heterogeneous, mostly unexplained by the wage, amenities and observed characteristics. An important part of this heterogeneity, though, could come from measurement error. In section 6, we shall show that the higher σ_z , the weaker wage/amenity correlation for job changers, when wage/amenity compensation is held constant. The above analysis thus suggests that measurement error, as well as “true” heterogeneity in mobility, biases compensating differentials towards zero in cross-section.

Wage/ amenity compensation: We now turn to the last three rows of Tables 7a-7c, which feature the γ_z , δ_z and δ_z^* estimates, for every country/amenity sample. We interpret these parameters as the effects of a wage increase or a rise or fall in satisfaction on the reservation wage. First, the estimates of the γ_z parameter range between .5 (Denmark) and .9 (France). All the parameters are strongly significant, confirming that, when unobserved heterogeneity is accounted for to control for differences in job offers, the current wage has a strong negative effect on job change propensity (see Table 6).

Next, Tables 7a-7c show that being satisfied with one’s job’s non-wage characteristic increases the reservation wage. This effect is common to all the countries and amenities that we consider. Moreover, the δ_z parameters are always significant at the 95% level, except for “distance to job” (in France for this amenity δ_z is significant at the 90% level). This result contrasts with the literature, as most studies on compensating differentials typically find an opposite or insignificant effect for some amenities. For instance, in Gronberg and Reed (1994) only two amenities over four find a positive and significant effect of amenities on job duration.

Our model also gives estimates of the individual wage/amenity trade-off in job offers. For the related parameter δ_z^* , the results are more ambiguous than in the case of current jobs’ characteristics. Yet, several cross-country regularities are worth noting.

First, the amenities “type of work” and “working conditions” exhibit high and

significant compensation. According to our model, workers weight positively both the wage and these amenities when deciding whether to accept a job offer. This intuitive result holds in every country we consider.

Then, results are more mixed for the amenities “working hours” and “working times”. The former shows significant compensation in Denmark and the Netherlands. As for France, the first four waves in the ECHP were misreported for this amenity, resulting in very few job changers and imprecise estimates. We do not report the results in this version of the paper. For the amenity “working times”, the δ_z^* estimates are also of the intuitive sign, except in France. In this case, note that the δ_z estimate is especially large (55% of the wage). The δ_z^* estimates for this amenity are always insignificant.

Lastly, the estimates for the amenities “distance to job” and “job security” are always positive, *i.e.* wrong-signed. In most cases, they are significant at the 95% level. We interpret these counter-intuitive results as arising from a probable omitted-variable bias. Lower risk aversion is likely to affect both the decision to change jobs (*ceteris paribus*) and the individual’s response to the question concerning job security. We confirmed this intuition by incorporating a public-sector dummy as a regressor in the mobility equation, as an imperfect proxy for risk aversion. The δ_z^* parameter was significantly reduced by this procedure. However, public-sector indicators (as type-of-contract variables) are also likely to be highly endogeneous in the regressions. We thus did not pursue this approach.²¹ A correct account of the role of job security perception in quit decision is left for future research.

The amenity “distance to job” also presents positive and mostly significant parameters. This is surprising, as this amenity stems from an “objective” feature of the job, and thus is likely to be perfectly foreseen by workers. We think that the omission of important economic variables for this amenity, such as geographic dummies and transportation facilities, can be responsible for our result. Unfortunately, the ECHP does not provide the relevant information for the analysis of commuting.

We can eventually draw three main conclusions from Tables 7a-7c:

- The current wage plays an important role in the job mobility decision ($\gamma_z > 0$),
- The current amenity *always* significantly increases workers’ reservation wage ($\delta_z > 0$),
- In several important cases, as for the amenities “type of work” and “working conditions”, the offered amenity significantly lowers workers’ reservation wage.

Therefore we reveal systematic and significant compensating differentials in individuals’ preferences. So far, the literature had found mixed evidence of wage/amenity

²¹Interestingly, Villanueva (2004), in a much simpler model, also finds wrong-signed estimates for wage/ job security compensation.

compensation. Our findings suggest much higher workers’ preferences for non-wage characteristics than previously thought.

5.3 Comparing amenities

The last part of this section is devoted to the comparison of non-wage characteristics in their relation to job mobility. Because of the complexity of the model and the small proportion of voluntary job changers in the sample, the analysis has been conducted separately for different amenities. Yet, all these characteristics are likely to enter workers’ utility, so that comparing our results for different amenities is worthwhile. In order to show that amenities are likely to enter worker’s utility differently, we first show that the determinants of the satisfaction variable differ with respect to the amenity. Then, we suggest a ranking of amenities, based on MWP’s and on their weight in job mobility decisions.

“Subjective heterogeneity” for different amenities: We here merge the different samples corresponding to different amenities, for a given country. We compare two amenities at a time. Two conclusions are salient. First, heterogeneity θ_1 is highly correlated between different samples.²² In Denmark, the correlation is .85 on average, in France it reaches .95. This suggests that this “productive” heterogeneity is mostly identified from the wage data. Second, the “subjective” heterogeneity variable θ_2 does differ from a sample to another. As Tables 8a-8c illustrate, the correlation ranges between .55 and .65, which are both well below 1. This suggests that the “subjective” preference for an amenity does vary among non wage characteristics, and is not a mere expression of global “satisfaction” with the job, or a psychological feature of the respondent. Amenities are thus likely to enter workers’ utility functions *differently*. In the next paragraph, we weight their respective influence on job mobility decisions.

<< Tables 8a-8c about here >>

Marginal Willingness to Pay: Tables 8a-8c rank the six amenity variables according to the MWP, for each country. The Marginal Willingness to Pay for the amenity in the current job (MWP) is computed as δ_z/γ_z . The MWP for the amenity in job offers (MWP*) is computed as $-\delta_z^*$. Both express percentages of the current or offered (monthly) wage.²³ There are two remarkable facts in these tables. First, the MWP’s are high for some amenities, such as “type of work” for which the average

²²To compute a “correlation” between two discrete variables $X, Y \in \{1, \dots, K\}$, we computed:

$$\frac{1}{K} \sum_k \mathbb{P}(X = k, Y = k),$$

which ranges between 0 and 1. We calculated this quantity by simulating groups for every worker in the sample.

²³A cross country analysis prevents us from multiplying these MWP’s by the mean wage since national currency was still legal tender in the 1990’s. MWP’s are thus given with respect to the logarithm of the wage.

MWP ranges between one third (offers) and two thirds (current job’s characteristics) of the wage. These results can be compared to van Ommeren *et al.* (1999), who find similar orders of magnitude for the amenity they consider. However, they strongly contrast with the hedonic literature, where orders of magnitude are usually much lower.

Second, the ranking of amenities is very similar in the countries we study, and for the two measures of MWP we compute. Clearly, as suggested in 5.2, the two most relevant amenities for job mobility decisions are “type of work” and “working conditions”, for which the MWP’s are a large proportion of the wage. Then come “working hours” and “working times”, with lower but mostly significant MWP’s. Lastly, as pointed out above, “distance to job” and “job security” are associated to positive MWP’s in the current job (significant for “job security”), and wrong-signed MWP’s in job offers.

Amenities and job mobility: We lastly compute the elasticities of job change propensity with respect to its various determinants. From (10), the elasticity with respect to y_{t+1}^* can be written:

$$\varepsilon = \frac{1}{\sigma_z} \frac{\phi}{\Phi} \left(\frac{y_{t+1}^* - x'_{it} \alpha_z - \gamma_z y_{it} - \delta_z a_{it} - \delta_z^* a_{it+1}^*}{\sigma_z} \right).$$

This elasticity represents the increase in the job change probability which would occur if the wage offer increased by 1%. The bottom lines of Tables 8a-8c show sample averages of these elasticities, for each country.²⁴ The results show high wage elasticities, ranging from 1.5 in France to 2.5 in Denmark. It is then straightforward to compute the elasticities with respect to other covariates, as the product of ε and the parameter estimate corresponding to the covariate. Tables 8a-8c unsurprisingly show high elasticities for the wage and amenity variables. Yet, the estimates are mostly insignificant at the 95% level. The last line features the mean elasticity with respect to age:

$$\varepsilon_{age} = -(\alpha_z(age) + 2 \times age \times \alpha_z(age^2))\varepsilon.$$

In every country, this elasticity is negative, though insignificant.

Therefore, the wage and non-wage job characteristics seem to have a strong impact on voluntary mobility. The Marginal Willingnesses to Pay for the six amenities are significant and large, at least when looking at current job’s characteristics, and elasticities are high. Nevertheless, the explanatory power of both the wage and the amenity variables is weak. A variance analysis that we performed shows that the percentage of variance explained by the wage is on average less than 25% of the part explained by age in the Netherlands and Denmark, and less than 10% in France. It

²⁴ As wage and amenity offers are not observed for job stayers, we simulated several wage/ amenity/ mobility trajectories for each individual in the sample, and computed elasticities. We found that, given the sample size, two simulations were enough to obtain good approximations of the parameter estimates. We bootstrapped this procedure 500 times with replacement to obtain the standard errors.

is also a very small percentage of the total variance, less than 5% in every country.²⁵ This result, together with the parameter estimates reported in 5.2, suggest that mobility costs are highly heterogeneous. Under these conditions, are the high MWP's computed in this section reflected in cross-section? Next section intends to build a bridge between the MWP methodology used here and the results of hedonic wage regressions.

6 Hedonic wage regressions and job mobility

Last section shows much higher and more significant wage/amenity compensation than found in the hedonic wage literature. Individuals trade off wage for better amenities when deciding whether to change jobs. Yet this notion of compensation is not what researchers, after Rosen (1974), usually refer to as compensating differentials. To compare our results to the hedonic wage literature, we here explain how the individual trade-off in job mobility decisions affects the observed wage/amenity correlation in cross-section. In particular, we show that in countries where voluntary job changes are rare, weak wage/amenity correlations can reflect high individual valuation of these two determinants in the mobility decision process.

6.1 The effect of mobility costs on observed compensating differentials

In this subsection we consider a simplified framework of job mobility decisions, while keeping the main features of the model. We use this simple setting to assess the extent to which wage/amenity compensation, as defined in this paper, and observed wage/amenity correlation, as studied in the hedonic wage literature, can differ in the presence of heterogeneous mobility costs.

Wage and amenity differentials: Let (y^*, u_a^*, u_z) be a trivariate normal distribution with mean $(\mu_y^*, 0, 0)$ and diagonal covariance matrix $diag((\sigma_y^*)^2, 1, \sigma_z^2)$. Wage offers are given by y^* , amenity offers satisfy:

$$a^* = \mathbf{1}\{\mu_a^* + u_a^* > 0\},$$

and the mobility decision variable is assumed to follow:

$$z = \mathbf{1}\{y^* > \mu_z + \delta_z^* a^* + u_z\}.$$

²⁵For this exercise, we decomposed the variance of the latent variable of the job mobility indicator z_{it} , as σ_z is identified. We did not take the covariances into account, since the correlations were small. Hence, for instance, the percentage of variance explained by the wage is by definition:

$$\frac{\mathbb{V}(y_{t+1}^* - \gamma_z y_t)}{\mathbb{V}(y_{t+1}^* - \tau_{a_t} a_{t+1}^*(y_t; x_t))}.$$

Since wage and amenity offers are not observed, we computed these quantities by simulation, as explained in footnote 24.

This framework can be interpreted as a version of the selection model of job mobility given by equations (5)-(6) and (10)-(11) in the case where workers are homogeneous, and there is no wage/ amenity correlation in job offers.

We define: $\sigma = \sqrt{(\sigma_y^*)^2 + \sigma_z^2}$, and: $\mu = \mu_z - \mu_y^*$. We think of μ as fixed mobility costs (net of the mean of offered wages) and of σ as heterogeneity in mobility costs.

Let us denote as y and a accepted wage/ amenity values. We are interested in the following quantity:

$$\Delta_z = \mathbb{E}(y|a = 1, z = 1) - \mathbb{E}(y|a = 0, z = 1),$$

which is the observed wage differential for job changers. Denoting the standard normal PDF (resp. CDF) as ϕ (respectively Φ), straightforward computation yields the following expressions:

$$\mathbb{E}(y|a, z = 1) - \mathbb{E}(y^*|a) = \frac{(\sigma_y^*)^2}{\sigma} \frac{\phi}{\Phi} \left(-\frac{\mu + \delta_z^* a}{\sigma} \right), \quad a = 0, 1,$$

and:

$$\frac{\mathbb{P}(a = 1|z = 1)}{\mathbb{P}(a^* = 1)} = \frac{\Phi \left(-\frac{\mu + \delta_z^*}{\sigma} \right)}{\Phi(\mu_a^*)\Phi \left(-\frac{\mu + \delta_z^*}{\sigma} \right) + \Phi(-\mu_a^*)\Phi \left(-\frac{\mu}{\sigma} \right)}.$$

In particular, the differential $\mathbb{E}(y|a, z = 1) - \mathbb{E}(y^*|a)$ is always positive. On average, the mean of accepted wages is higher than the wage offers mean. We shall refer to this effect, which arises from the selection rule, as wage gains associated with voluntary job mobility. Similarly, wage/ amenity compensation ($\delta_z^* < 0$) implies that $\mathbb{P}(a = 1|z = 1) > \mathbb{P}(a^* = 1)$, so that, on average, job changes are also associated with improvements in the satisfaction with non-wage characteristics.

Lastly, the wage differential:

$$\Delta_z = \frac{(\sigma_y^*)^2}{\sigma} \left[\frac{\phi}{\Phi} \left(-\frac{\mu + \delta_z^*}{\sigma} \right) - \frac{\phi}{\Phi} \left(-\frac{\mu}{\sigma} \right) \right],$$

is *negative* when δ_z^* is negative, since the inverse Mill's ratio is strictly decreasing on the real line. Therefore, in this simple setting, wage/ amenity compensation in job change decisions translates into negative wage/ amenity correlation.

Orders of magnitude: We can gain much understanding by studying the order of magnitude of these differentials.²⁶ Empirically, the probability of job change is less than 5% in the four countries we consider in this paper, conditional on “good” ($a = 1$) or “bad” ($a = 0$) amenity offers. For such values of p , $\frac{\phi}{\Phi}(\Phi^{-1}(p))$ is close to $-\Phi^{-1}(p)$,²⁷ so that we can approximate Δ_z as:

$$\Delta_z \approx \left(\frac{\sigma_y^*}{\sigma} \right)^2 \delta_z^*.$$

²⁶Note that, unlike in the previous paragraph, the assumption of normally distributed residuals is here critical.

²⁷As $\frac{\phi}{\Phi}(x) = -x + o(x)$ when $x \rightarrow -\infty$.

When the aggregate probability of job change is small, the wage differential for job changers is the product of amenity compensation (δ_z^*) and the ratio $\left(\frac{\sigma_y^*}{\sigma}\right)^2 = \frac{(\sigma_y^*)^2}{\sigma_z^2 + (\sigma_y^*)^2}$. Now, this last quantity is the R-squared in the OLS regression of the decision variable z on the wage offer y^* . The better y^* predicts job-to-job mobility, the closer to one this ratio is. Empirically, the wage predicts job mobility rather poorly (see the previous section) and this ratio ranges between .01 and .04. This quantity is exactly the amount by which wage/ amenity compensation is reduced when one looks at Δ_z .

To illustrate this order of magnitude, consider the following numerical values for the model parameters:

$$\mu_y^* = 8, \quad \mu_z = 10, \quad \sigma_z = 1, \quad \sigma_y^* = .20, \quad \mu_a^* = 0, \quad \delta_z^* = -.20 \quad .$$

These values correspond roughly to the mean of the model estimates over the three countries. For these values, $\left(\frac{\sigma_y^*}{\sigma}\right)^2$ is .04 and fixed costs are $\mu = 2$. Wage gains from job mobility are thus approximately of 8%, and amenity gains are of 20%. Yet, the wage/ amenity compensation ($|\delta_z^*|$) of 20% is reflected in cross-section as a wage differential (δ_z) of less than 1%. Although the correlation is indeed negative as the theory implies, it is of very small size and unlikely to be detected by cross-sectional regressions.

Figures 2a and 2b present the wage offer distribution, and the same distribution conditional on changing jobs to a given amenity $a = 0$ or $a = 1$.²⁸ In Figure 2a, the parameters are calibrated as above. Both conditional distributions are significantly to the right of the wage offer curve. Yet, they are almost identical, even if careful examination shows that the curve for $a = 0$ is (very slightly) to the right of the wage density for $a = 1$. In this economy, in spite of strong individual valuation for non-wage characteristics (recall that $\delta_z^* = -.20$), there are virtually no compensating differentials in cross-section.

<< **Figures 2a and 2b about here** >>

The situation changes radically in Figure 2b, where we have set μ to .5 and σ to .25, so that the aggregate probability of job-to-job mobility is similar but mobility costs are lower and more homogeneous. There, compensating differentials are clearly apparent on the Figure.

In this paragraph we have assumed zero correlation in wage/ amenity offers. In the rest of this section, we relax this assumption, and present the results of hedonic wage regressions for job stayers and job changers respectively. Our model allows us to perform all these computations analytically.

6.2 Hedonic wage regression results

We here generalize the insights of 6.1 to the more general model (1)-(14), and provide an analytical decomposition of various wage differentials we are interested in.

²⁸We compute conditional wage distributions using Bayes' formula.

Analytical expressions of compensating differentials: Returning to the global model (1)-(14), let $\tilde{x}_t = \{x_t, a_t, y_t\}$ be the set of individual and (current) job's characteristics. We are interested in two different wage differentials:

$$\Delta = \mathbb{E}(y_{t+1}|a_{t+1} = 1, z_t = 0, x_{t+1}, \theta_t) - \mathbb{E}(y_{t+1}|a_{t+1} = 0, z_t = 0, x_{t+1}, \theta_t),$$

and:

$$\Delta_z = \mathbb{E}(y_{t+1}|a_{t+1} = 1, z_t = 1, \tilde{x}_t, \theta_t) - \mathbb{E}(y_{t+1}|a_{t+1} = 0, z_t = 1, \tilde{x}_t, \theta_t).$$

Δ is the compensating differential for job stayers, computed at the individual level. Since job changes are rare in the data, it is closely related to what the hedonic wage approach focuses on, namely a measure of cross-sectional wage/ amenity correlation. The differential Δ_z is the same quantity, computed conditionally on (voluntary) job change.

The structure of the model allows us to compute these differentials analytically. Indeed, combining equations (1) and (2) using Assumption (16) we obtain:

$$\Delta = \sigma_y^r \rho_{ya}^r \left[\frac{\phi}{\Phi} \left(-(x'_{t+1} \alpha_a^r + \beta_{1a}^r \theta_{1t} + \theta_{2t}) \right) - \frac{\phi}{\Phi} \left(x'_{t+1} \alpha_a^r + \beta_{1a}^r \theta_{1t} + \theta_{2t} \right) \right].$$

Moreover, in the general case where wage and amenity offers are correlated, the wage differential Δ_z can be decomposed as follows, combining (5), (6) and (10):

$$\Delta_z = \Delta_z^z + \Delta_z^\rho,$$

where:

$$\Delta_z^z = \frac{(\sigma_y^*)^2}{\sigma} \left[\frac{\phi}{\Phi} \left(-\frac{x'_t(\alpha_z - \alpha_y^*) - \beta_y^* \theta_{1t} + \gamma_z y_t + \delta_z a_t + \delta_z^*}{\sigma} \right) - \frac{\phi}{\Phi} \left(-\frac{x'_t(\alpha_z - \alpha_y^*) - \beta_y^* \theta_{1t} + \gamma_z y_t + \delta_z a_t}{\sigma} \right) \right],$$

is the wage differentials for job changers, would here be no correlation in job offers. Using formulas to compute the moments of truncated binormal distributions (see *e.g.* Maddala, 1983) we also can express the second term analytically. Appendix F gives the exact analytical expression of Δ_z^ρ . This second term can be understood as the effect of correlation in job offers on compensating differentials. Thus, in the model, compensating differentials for job changers have two origins: a labor supply effect, arising from workers' valuation of wage and non-wage characteristics (Δ_z^z), and a labor demand effect, which stems from the structure of job offers posted by the firms (Δ_z^ρ). The next paragraph presents our estimates of these different effects.

Empirical results: Table 9 shows sample means of the wage differential Δ , computed for every country and amenity.²⁹ The results do not show unambiguous negative wage/ amenity correlation. For the amenities "type of work" and "working

²⁹To compute standard errors, we proceeded as indicated in footnote 24.

conditions”, the correlation is positive in every country. For the latter, it is significant. On the other hand, “working hours”, “working times” and “distance to job”, exhibit negative and significant correlation. These results are consistent with the (inconclusive) results of the hedonic wage literature.

<< **Table 9 about here** >>

Focusing on voluntary job changers yields a clearer conclusion, as the differentials Δ_z^z are often negative, consistently with wage/ amenity compensation on the (labor) supply side. These differentials are of the sign of δ_z^* . Hence, for the amenities “type of work” and “working conditions”, the differences are negative in every country, significantly so in Denmark and the Netherlands. This conclusion is also valid for “working hours” and “working times”, except in France for the latter where Δ_z^z is positive, although insignificant.

However, the evidence of negative correlation for voluntary job changes is mixed, to put it mildly. Two effects mitigate the “supply” effect of workers’ compensation. First, as pointed out in 6.1, heterogeneity in mobility costs significantly reduces this effect. Comparing Tables 9 to Tables 8a-8c shows that Marginal Willingnesses to Pay of .30 translate into correlations of minus than .02. Comparing these Tables is interesting, as the difference gives a rough measure of the constraints on job-to-job mobility on the labor market. Moreover, these tables provide a comparison of the two methodologies to estimate wage/ amenity compensation in the literature: Tables 8a-8c illustrate the approach based on job duration, and Table 9 gives an illustration of the hedonic wage methodology.

A second effect can empirically mitigate the low but negative wage/ amenity correlation for job changers. Table 9 shows the correlation arising from the (labor) “demand” effect, *i.e.* from the correlation in job offers. Estimates of Δ_z^e are sometimes significant in Denmark and the Netherlands, but no clear conclusion arises from the sign of these expressions. In France, the terms are all insignificant. These results follow closely the ρ_{ya}^* estimates presented in Tables 7a-7c (see Section 5.2).

Thus, evidence of wage/ amenity compensation is rather weak in cross-section, although the “true” valuation of non-wage characteristics is not negligible. Individual compensation for bad or good amenities translates into a much smaller, admittedly still negative, correlation. This section has highlighted two key elements in this mechanism: the low explanatory power of the wage and amenities in job mobility decisions (high σ_z), and the often insignificant correlation in job offers (low $|\rho_{ya}^*|$). Our results thus shed light on the difficulty of finding compensating differentials in cross-section, even conditional on unobserved heterogeneity, and even if individuals value non-wage characteristics significantly in relation to the wage.

7 Conclusion

The theory of compensating differentials builds on Adam Smith’s famous statement:³⁰

“The whole of the advantages and disadvantages of the different employments of labour and stock must, in the same neighborhood, be either perfectly equal or continually tending to equality.”

On the labor market, this implies that bad non-monetary characteristics of one’s job must be compensated by higher wages. However, empirical tests of the theory have proven disappointing so far, finding non-significant or even wrong-signed wage/amenity correlations.

In this paper, we claim that these correlations must not be interpreted as reflecting individual preferences over non-wage amenities. Smith had indeed pointed out the conditions under which the *“equality of advantages and disadvantages”* was to be expected:

“This at least would be the case in a society where things were left to follow their natural course, where there was perfect liberty, and where every man was perfectly free both to choose what occupation he thought proper, and to change it as often as he thought proper.”

In modern economies, very low rates of voluntary mobility suggest that workers are far from being *“perfectly free”* to change jobs. Consequently, the predictions of the theory of compensating differentials are unlikely to hold.

Our estimation results show significant valuation of non-wage characteristics, in spite of low wage/amenity correlations. The orders of magnitude we obtain are higher than usual estimates in the literature. However, the low explanatory power of both the wage and amenities on job mobility, and the absence of compensation on the demand side, imply that these individual preferences do not translate into significant negative correlation. We view these results as an encouraging step towards the understanding of which characteristics workers actually value in their jobs. Our findings empirically confirm that the analysis of inequality or mobility on the labor market should not be based on the wage alone and that non-monetary characteristics do enter workers’ job valuation and mobility decisions.

Still, our method suffers from several limitations. First, our reservation wage modeling does not permit to disentangle the effects of mobility costs and individual preferences on job change decisions. To do so, we would need exclusion restrictions which are difficult to justify.³¹ Another possibility would be to use data on transition costs. Yet, mobility costs are at least partly psychological, which complicates the researcher’s task.³² The second limitation stems from the size of our samples which prevents us from modeling the influence of several amenities on job mobility. We have

³⁰*An Inquiry Into the Nature and Causes of the Wealth of Nations*, Book 1, Chapter 10, Introduction.

³¹See *e.g.* the use of the “children” and “work attachment” indicators as exclusion variables in Groot and Verbeke (1997).

³²See *e.g.* the literature on the so-called “*status-quo bias*”.

here estimated our model on a standard Labor Force Survey but we think our method could be easily augmented in order to overcome the limits mentioned above, with a richer and more specific dataset on workers' preferences and mobility costs. Lastly, workers' preferences could be introduced in the demand side of the labor market in order to give microeconomic foundations to the wage/ amenity offer distributions we have used. Linking our approach to more structural models derived from the equilibrium job search literature could be quite relevant for the construction and estimation of a general equilibrium model with multiple job characteristics.

References

- [1] Altonji, J., and C. Paxson (1988): "Labor Supply Preferences, Hours Constraints, and Hours-Wage Trade-Offs," *Journal of Labor Economics*, 6, 254-276.
- [2] Brown, C. (1980): "Equalizing Differences in the Labor Market," *The Quarterly Journal of Economics*, 94, 113-134.
- [3] Carneiro P., Hansen K. T. and Heckman J. J. (2002): "Estimating Distributions of Treatment Effects with an Application to the Returns to Schooling and Measurement of the Effects of Uncertainty on College Choice," *International Economic Review*, 44(2), 361-422.
- [4] Clark, A. E., and A. J. Oswald (1994): "Unhappiness and Unemployment," *The Economic Journal*, 104, 648-659.
- [5] Connolly, H., and P. Gottschalk (2002): "Job Search with Heterogeneous Wage Growth - Transitions to "Better" and "Worse" Jobs," Boston College Working Paper.
- [6] Dempster, A. P., N. M. Laird and D. B. Rubin (1977): "Maximum Likelihood from Incomplete Data via the EM Algorithm," *Journal of the Royal Statistical Society*, B 39(1), 1-38.
- [7] 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, 366-379.
- [8] Flinn C. J., and J. J. Heckman (1982): "New Methods for Analyzing Structural Models of Labor Force Dynamics," *Journal of Econometrics*, 18, 115-168.
- [9] Godderis, J. H. (1988): "Compensating Differentials and Self-Selection: An Application to Lawyers," *The Journal of Political Economy*, 96, 411-428.
- [10] Gronberg, T., and R. Reed (1994): "Estimating Workers' Marginal Willingness to Pay for Job Attributes Using Duration Data," *Journal of Human Resources*, 29, 911-931.
- [11] Groot, W., and M. Verbene (1997): "Aging, Job Mobility, and Compensation," *Oxford Economic Papers*, New Series, 49, 380-403.
- [12] Hammermesh, D. S. (1999): "The Changing Inequality for Workplace Amenities," *The Quarterly Journal of Economics*, 114, 1085-1123.

- [13] Heckman, J. J. (1974): "Shadow Prices, Market Wages, and Labor Supply," *Econometrica*, 42, 679-694.
- [14] Heckman, J. J. (1976): "The Common Structure of Statistical Models of Truncation, Sample Selection and Limited Dependent Variables and a Simple Estimator for Such Models," *Annals of Economic and Social Measurement*, 5, 475-492.
- [15] Heckman, J., and B. Singer (1984): "A Method for Minimizing the Impact of Distributional Assumptions in Econometric Models for Duration Data," *Econometrica*, 52(2), 271-320.
- [16] Hwang, H.S., D. Mortensen, and W.C. Reed. (1998): "Hedonic Wages and Labor Market Search," *Journal of Labor Economics*, 16, 815-847.
- [17] Hwang, H. S., W. C. Reed, and C. Hubbard (1992): "Compensating Differentials and Unobserved Productivity," *The Journal of Political Economy*, 100, 835-858.
- [18] Kostiuk, P. F. (1990): "Compensating Differentials for Shift Work," *The Journal of Political Economy*, 98, 1054-1075.
- [19] Kotlarski, I. (1967): "On Characterizing the Gamma and Normal Distribution," *Pacific Journal of Mathematics*, 20, 69-76.
- [20] Lang, K., and S. Majumdar (2004): "The Pricing of Job Characteristics When Markets do not Clear: Theory and Policy Implications," *International Economic Review*, 45, 1111-1128.
- [21] Maddala G. S. (1983): *Limited Dependent and Qualitative Variables in Econometrics*, Cambridge University Press.
- [22] Manski, C. F. (1988): "Identification of Binary Response Models," *Journal of the American Statistical Association*, 83, 729-738.
- [23] Nelson, F. D. (1977): "Censored Regression Models with Unobserved Stochastic Censoring Thresholds," *Journal of Econometrics*, 6, 309-327.
- [24] Postel-Vinay, F., and J.M. Robin (2002): "Equilibrium Wage Dispersion with Worker and Employer Heterogeneity," *Econometrica*, 70, 2295-2350.
- [25] Rosen, S. (1974): "Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition," *Journal of Political Economy*, 82, 34-55.
- [26] Rosen, S. (1986): "The Theory of Equalizing Differences," in O. Ashenfelter and D. Card, eds., *Handbook of Labor Economics* vol 1: 2 641-692. Amsterdam: Elsevier Science.
- [27] Senick, C. (2003): "What Can We Learn from Subjective Data: the Case of Income and Well-Being," *Journal of Economic Surveys*, forthcoming.
- [28] Smith, A.: *An Inquiry into the Nature and Causes of the Wealth of Nations*, 1776.
- [29] Van Ommeren, J., Van den Berg, G., and C. Gorter (2000): "Estimating the Marginal Willingness to Pay for Commuting," *Journal of Regional Science*, 40, 541-563.
- [30] Van Praag, B. (1991): "Ordinal and Cardinal Utility," *Journal of Econometrics*, 50, 69-89.

- [31] Villanueva E. (2004): “Compensating Wage Differentials and Voluntary Job Changes: Evidence from West Germany,” *mimeo* UPF.
- [32] Xenogiani, T. (2003): “Job Satisfaction, Mobility Decisions and Wage Gains by Gender,” LSE Working Paper.

APPENDIX

A Data

The definition of jobs: We let individuals be in either one of the two following labor market states: employed or unemployed. Unemployment comprises self declared unemployment, inactivity, employment during less than 15 hours per week or with wages lower than the first percentile (which, for example, is around 235 Euros per month in France, that is 25% of the median wage). We drop every individual who experiences a self employment spell since we assume her trajectory (and especially her job mobility decisions) not to be governed by the same processes as those of workers in paid employment.

Attrition: Some of the observation periods are right censored, *i.e.* individuals do not always stay in the ECHP during the eight waves. We assume this right censoring to be exogenous to the wage, amenity and job mobility process.

Missing data: The problem of missing data is twofold: there can be non reported variables for a given wave where the individual is present or the individual can “disappear” from the survey during a year within his observation period and come back one year later. When it is possible, we impute missing data on wages and/ or amenity using the previous or following wave if the individual is still in the same job: we substitute the missing wage for the mean of the previous and following wage and draw the amenity from a binomial distribution weighting both the previous and following amenity with probability 0.5 (the amenity can change within a job). These substitutions affect less than a thousand observations (over *e.g.* more than 30 000 in France). For the few observations that still show missing data, we create two individuals out of one. This rather arbitrary treatment of less than 1% of our sample does not affect the consistency of the ML estimates and the loss of efficiency is likely to be small.

Misreporting of amenities: In France, the first wave shows major differences with the next ones when looking at amenities. We thus keep the last seven waves for all amenities but “working hours” in France. This last amenity is never reported as satisfying in the first four waves. We did not find a proper way to deal with this data failure and thus chose not to report the results for “working hours” in France.

B Generalized reservation wages

In this section of the Appendix, we derive the generalized reservation wages introduced in 3.1.

Let \mathcal{Y} be a subset of the real line \mathbb{R} , endowed with the canonical order \leq , and \mathcal{A} be a set. Let $y_1 \in \mathcal{Y}$ be the wage of an individual in a given job, and $a_1 \in \mathcal{A}$ be her level of job amenity. Suppose that this individual can decide whether or not to move to the alternative job (y_2, a_2) . Her decision process can be represented by the following relation:

$$\rightarrow: \{\mathcal{Y} \times \mathcal{A}\}^2 \rightarrow \{0, 1\}.$$

Therefore an individual employed in (y_1, a_1) changes to the alternative (y_2, a_2) if and only if $(y_1, a_1) \rightarrow (y_2, a_2)$. We impose the two following properties on \rightarrow :

Property 1 (Monotonicity) For all (a_1, a_2) in \mathcal{A}^2 , and (y_1, y_2, y_3) in \mathcal{Y}^3 . If: $(y_1, a_1) \rightarrow (y_2, a_2)$ and $y_3 \geq y_2$, then $(y_1, a_1) \rightarrow (y_3, a_2)$.

Property 2 (Continuity) $\{y_2 \in \mathcal{Y}, (y_1, a_1) \rightarrow (y_2, a_2)\}$ is a closed subset of \mathcal{Y} , for all (y_1, a_1, a_2) in $\mathcal{Y} \times \mathcal{A}^2$.

Property 1 is a weak transitivity assumption on the mobility decisions. It states that, given that an individual is willing to move from job 1 to job 2, she will decide to move from 1 to any job 3 offering a better wage and the same amenity level as 2. Property 2 is technical.

The next theorem shows that every binary relation satisfying properties 1 and 2, can be represented by a set of functions $\{\tau_{a_1, a_2} : \mathcal{Y} \rightarrow \mathcal{Y} \cup \{+\infty\}\}_{a_1, a_2}$:

Theorem 3 Let \mathcal{Y} be a connected subset of \mathbb{R} bounded from below, and \mathcal{A} be a set. Then \rightarrow satisfies properties 1 and 2 if and only if there exists a set of functions

$$\{\tau_{a_1, a_2} : \mathcal{Y} \rightarrow \mathcal{Y} \cup \{+\infty\}\}_{(a_1, a_2) \in \mathcal{A}^2},$$

such that:

$$(y_1, a_1) \rightarrow (y_2, a_2) \quad \text{iff} \quad y_2 \geq \tau_{a_1, a_2}(y_1),$$

for all (a_1, a_2) in \mathcal{A}^2 , and (y_1, y_2) in \mathcal{Y}^2 .

Proof.

The "if" part of the theorem is straightforward. First, as $y_2 \geq \tau_{a_1, a_2}(y_1)$ and $y_3 \geq y_2$ imply $y_3 \geq \tau_{a_1, a_2}(y_1)$, property 1 is verified. Second, $\{y_2 \in \mathcal{Y}, y_2 \geq \tau_{a_1, a_2}(y_1)\}$ is trivially closed so property 2 holds.

For the "only if" part, let us assume that \rightarrow satisfies properties 1 and 2. Let $y_1 \in \mathcal{Y}$ and $(a_1, a_2) \in \mathcal{A}^2$. Let $Acc_{(y_1, a_1)}(a_2) = \{y_2 \in \mathcal{Y}, (y_1, a_1) \rightarrow (y_2, a_2)\}$ be the set of jobs accepted by an individual with (y_1, a_1) , with amenities $a_2 \in \mathcal{A}$. Let us define the mapping τ_{a_1, a_2} :

$$\begin{aligned} \mathcal{Y} &\rightarrow \mathcal{Y} \cup \{+\infty\} \\ y_1 &\mapsto \text{Inf} Acc_{(y_1, a_1)}(a_2). \end{aligned}$$

As $Acc_{(y_1, a_1)}(a_2)$ is closed, $\tau_{a_1, a_2}(y_1)$ is the minimum of this set. As property 1 holds, it thus follows that $Acc_{(y_1, a_1)}(a_2) = [\tau_{a_1, a_2}(y_1), +\infty[$. ■

C Presentation of the global model

We here describe the global model of wages, amenities and job mobility. The likelihood of an individual observation at a given job, conditional on the initial state, writes:

$$f(\theta_{1iT_{i0}}, \theta_{2iT_{i0}} | y_{iT_{i0}}, a_{iT_{i0}}, x_{iT_{i0}}) \prod_{t=T_{i0}}^{T_{i1}-1} f(y_{it+1}, a_{it+1}, z_{it}, c_{it}, \theta_{1it+1}, \theta_{2it+1} | y_{it}, a_{it}, \theta_{1it}, \theta_{2it}, x_{it}, x_{it+1}), \quad (\text{C1})$$

where (y_{it}, a_{it}) is the pair of job/amenities of individual i at t , c_{it} and z_{it} are the indicator variables indicating if the individual has been constrained during her job-to-job transition (c_{it}), or if she has changed job voluntarily (z_{it}) between t and $t + 1$, and $(\theta_{1it}, \theta_{2it})$ is the quality of the match at t . $[T_{i0}, T_{i1}]$ is the observation length for individual i . The factorization in (C1) comes from the first-order Markov property. In this part of the Appendix, we write down all the equations for the different individual processes at work:

1. mobility: match quality

$$\begin{aligned} \theta_{1it+1} &= x'_{it+1} \alpha_{\theta_1} + \gamma_{\theta_1} y_{it} + u_{y_{it+1}}, \\ \theta_{2it+1} &= x'_{it+1} \alpha_{\theta_2} + \beta_{\theta_2} \theta_{1it+1} + \delta_{\theta_2} a_{it} + u_{a_{it+1}}, \end{aligned}$$

if $c_{it} = 1$, $z_{it} = 1$, or $t = T_{i0} - 1$. $u_{y_{t+1}}, u_{a_{t+1}}$ are *i.i.d.*, independent of covariates, and allowed to be correlated.³³

2. probability of constrained job change

$$c_{it} = \mathbf{1} \{ x'_{it} \alpha^c + \beta^c \theta_{1it} + u_{it}^c > 0 \},$$

with u_{it}^c *i.i.d.* independent of x_t and θ_{1t} .

3. constrained job change: wage/amenity

$$\begin{aligned} y_{it+1} &= x'_{it} \alpha_y^c + \beta_y^c \theta_{1it} + u_{y_{it+1}}^c, \\ a_{it+1} &= \mathbf{1} \{ x'_{it} \beta_a^c + \beta_{1a}^c \theta_{1it} + \beta_{2a}^c \theta_{2it} + u_{ait}^c > 0 \}, \end{aligned}$$

if $c_{it} = 1$. $u_{y_{it+1}}^c, u_{ait}^c$ are *i.i.d.*, independent of covariates, and allowed to be correlated.

4. probability of voluntary mobility

$$\begin{aligned} z_{it} &= \mathbf{1} \{ x'_{it} \alpha_y^* + \beta_y^* \theta_{1it} + u_{y_{it+1}}^* > x'_{it} \alpha_z + \gamma_z y_{it} + \delta_z a_{it} \\ &\quad + \delta_z^* \mathbf{1} \{ x'_{it} \alpha_a^* + \beta_{1a}^* \theta_{1it} + \beta_{2a}^* \theta_{2it} + u_{ait}^* > 0 \} + u_{z_{it}} \}, \end{aligned}$$

if $c_{it} = 0$. $u_{z_{it}}$ is *i.i.d.* and independent of θ , y_t , x_t , a_t , $u_{y_{it+1}}^*$ and u_{ait}^* . $u_{y_{it+1}}^*, u_{ait}^*$ are *i.i.d.*, independent of the covariates and possibly correlated.

5. voluntary mobility: wage/ amenity

$$\begin{aligned} y_{it+1} &= x'_{it} \alpha_y^* + \beta_y^* \theta_{1it} + u_{y_{it+1}}^*, \\ a_{it+1} &= \mathbf{1} \{ x'_{it} \alpha_a^* + \beta_{1a}^* \theta_{1it} + \beta_{2a}^* \theta_{2it} + u_{ait}^* > 0 \}, \end{aligned}$$

if $c_{it} = 0$ and $z_{it} = 1$.

³³We impose the correlation between wage/ amenity values and match quality to be the same after a constrained or a voluntary transition. We also assume that the same correlation holds for the first date of observation. These simplifications had virtually no effect on the results.

6. no job change: match quality

$$\theta_{1it+1} = \theta_{1it},$$

$$\theta_{2it+1} = \theta_{2it},$$

if $c_{it} = 0$ and $z_{it} = 0$

7. no job change: wage/ amenity

$$y_{it+1} = x'_{it+1}\alpha_y^r + \theta_{1it+1} + u_{yit+1}^r,$$

$$a_{it+1} = \mathbf{1} \{x'_{it+1}\alpha_a^r + \beta_{1a}^r\theta_{1it+1} + \theta_{2it+1} + u_{ait+1}^r > 0\},$$

if $c_{it} = 0$ and $z_{it} = 0$. u_{yit+1}^r, u_{ait+1}^r are *i.i.d.*, independent of $\theta_{t+1}, x_{t+1}, u_{yt}^*, u_{at}^*$ and u_{zt} , and possibly correlated.

D The estimation procedure

D.1 The EM algorithm

In this section of the Appendix, we detail the estimation procedure of the global model presented above (Appendix C).

Consider an individual i , and a given job which lasts from t_{i0} to $t_{i1} - 1$. Match quality is assumed discrete: $(\theta_1, \theta_2) \in \{1 \dots K_1\} \times \{1 \dots K_2\}$. Match quality is constant on $[t_{i0} + 1, t_{i1}]$. It is thus convenient to estimate the incomplete likelihood (Dempster *et al.*, 1977) of the individual observation between $t_{i0} + 1$ and t_{i1} , conditional on covariates and wage/ amenity realizations at t_{i0} :

$$\sum_{\theta_1, \theta_2} \frac{\pi_{\theta_1, \theta_2} f(y_{it_{i0}}, a_{it_{i0}} | \theta_1, \theta_2, x_{it_{i0}}; \Theta_1)}{\sum_{k_1, k_2} \pi_{k_1, k_2} f(y_{it_{i0}}, a_{it_{i0}} | k_1, k_2, x_{it_{i0}}; \Theta_1)} \prod_{t=t_{i0}}^{t_{i1}-1} f(y_{it+1}, a_{it+1}, c_{it}, z_{it} | y_{it}, a_{it}, \theta_1, \theta_2, x_{it}; \Theta_2),$$

where Θ_1 and Θ_2 are sets of parameters, and π_{k_1, k_2} are the prior probabilities $\mathbb{P}(\theta_{1it} = k_1, \theta_{2it} = k_2)$.

Note that:

$$\frac{\pi_{\theta_1, \theta_2} f(y_{it_{i0}}, a_{it_{i0}} | \theta_1, \theta_2, x_{it_{i0}}; \Theta_1)}{\sum_{k_1, k_2} \pi_{k_1, k_2} f(y_{it_{i0}}, a_{it_{i0}} | k_1, k_2, x_{it_{i0}}; \Theta_1)},$$

is the (posterior) probability that the groups equal θ_1 and θ_2 given the first observation. The unit of observation is thus taken as $[t_{i0} + 1, t_{i1}]$, and the whole study is conducted conditional on the information at t_{i0} .

Given initial values for the parameters, $\Theta_1^{(s)}$ and $\Theta_2^{(s)}$, the two steps of EM write as follows.

E-Step: Compute the posterior probabilities of (θ_1, θ_2) given the data $X_i = \{y_{it}, a_{it}, c_{it}, z_{it}\}_{t_{i0}+1 \leq t \leq t_{i1}}$ and $X_{i0} = \{y_{it_{i0}}, a_{it_{i0}}\}$, and conditional on $x_i = \{x_{it}\}_{t_{i0} \leq t \leq t_{i1}}$ and $x_{i0} = x_{it_{i0}}$, as:

$$p_{\theta_1, \theta_2}^{(s)}(X_i) = \frac{f(\theta_1, \theta_2 | X_{i0}, x_{i0}; \Theta_1^{(s)}) f(X_i | \theta_1, \theta_2, x_i; \Theta_2^{(s)})}{\sum_{k_1, k_2} f(k_1, k_2 | X_{i0}, x_{i0}; \Theta_1^{(s)}) f(X_i | k_1, k_2, x_i; \Theta_2^{(s)})},$$

where:

$$f(\theta_1, \theta_2 | X_{i0}, x_{i0}; \Theta_1^{(s)}) \equiv \frac{\pi_{\theta_1, \theta_2} f(X_{i0} | \theta_1, \theta_2, x_{i0}; \Theta_1)}{\sum_{k_1, k_2} \pi_{k_1, k_2} f(X_{i0} | k_1, k_2, x_{i0}; \Theta_1)}.$$

M-step: Update the parameters as follows:

$$\pi_{\theta_1, \theta_2}^{(s+1)} = \frac{1}{N} \sum_{i, J(i)} p_{\theta_1, \theta_2}^{(s)}(X_{i.}), \quad (D2)$$

$$\Theta_1^{(s+1)} = \underset{\Theta_1}{\text{Argmax}} \sum_{i, J(i)} \sum_{\theta_1, \theta_2} p_{\theta_1, \theta_2}^{(s)}(X_{i.}) \ln f(X_{i0} | \theta_1, \theta_2, x_{i0}; \Theta_1), \quad (D3)$$

$$\Theta_2^{(s+1)} = \underset{\Theta_2}{\text{Argmax}} \sum_{i, J(i)} \sum_{\theta_1, \theta_2} p_{\theta_1, \theta_2}^{(s)}(X_{i.}) \sum_{t=t_{i0}}^{t_{i1}-1} \ln f(y_{it+1}, a_{it+1}, z_{it}, c_{it} | y_{it}, a_{it}, \theta_1, \theta_2, x_{it}; \Theta_2), \quad (D4)$$

where $J(i)$ are the jobs held by individual i .

Computation (D2) is straightforward. Instead of directly modeling the conditional density of (θ_1, θ_2) on the initial wage and amenity levels as in (7)-(8), we modeled the density of initial conditions conditional on θ , $f(X_{i0} | \theta_1, \theta_2, x_{i0}; \Theta_1)$. We model the wage density by OLS, and the amenity probability by PROBIT. This method, unlike the direct modeling aforementioned, resulted in a very stable algorithm.

To perform maximization (D4), we use a combination of OLS and PROBIT, weighted by the posterior probabilities, to update all the parameters of the global model, except the ones featured in the selection part of the model. Estimation of the latter presents particular computational difficulties (see Appendix D.2).

To make estimation faster, we proceeded in two stages. In a first stage, we estimated the global model assuming no selection effects in the voluntary mobility process, *i.e.* we replaced (5), (6) and (10) with:

$$\begin{aligned} y_{it+1}^* &= x'_{it+1} \tilde{\alpha}_y + \tilde{\beta}_y \theta_{1it+1} + \epsilon_{yit+1}, \\ a_{it+1}^* &= \mathbf{1} \left\{ x'_{it+1} \tilde{\alpha}_a + \tilde{\beta}_{1a} \theta_{1it+1} + \tilde{\beta}_{2a} \theta_{2it+1} + \epsilon_{ait+1} > 0 \right\}, \\ z_{it} &= \mathbf{1} \left\{ x'_{it} \tilde{\alpha}_z + \tilde{\beta}_z \theta_{1it} + \epsilon_{zit} > 0 \right\}, \end{aligned}$$

where ϵ_y , ϵ_a and ϵ_z are normally distributed, *i.i.d.*, independent of the covariates *and* independent of one another.

We then computed the posterior probabilities for every individual in the sample, and maximized the likelihood of the selection model, weighted by these probabilities. We then plugged the obtained estimates as initial values for the likelihood of the global model. Our experiments showed that the number of iterations necessary for EM to converge numerically was much reduced by proceeding this way.

Estimating this algorithm for each country/amenity sample could in theory permit the estimation of standard errors by usual moment conditions. However this computation proved to be intractable. We therefore present the ML standard errors of the parameters in (5)-(6) and (10)-(11), which do not account for the variability of the unobserved groups' estimates (the prior probabilities).

D.2 The censored regression model

The likelihood of the selection part of the model, for one transition $t/ t+1$, conditional on $(x_{it}, c_{it} = 0, \theta_{1it} = \theta_1, \theta_{2it} = \theta_2)$ and (y_{it}, a_{it}) writes:

$$\begin{aligned} \mathcal{L} &= \prod_i f(y_{it+1}, a_{it+1}, z_{it}), \\ &= \prod_{i, z_{it}=1} f_{z|y^*, a^*}(z_{it} = 1 | y_{it+1}, a_{it+1}) \prod_{i, z_{it}=1} f_{y^*, a^*}(y_{it+1}, a_{it+1}) \\ &\quad \times \prod_{i, z_{it}=0} f_z(z_{it} = 0) \prod_{i, z_{it}=0} f_{y^r, a^r|z}(y_{it+1}, a_{it+1} | z_{it} = 0), \end{aligned} \quad (D5)$$

where we dropped the conditioning variables for simplicity.

From Condition (16), the fourth term on the Right-Hand Side of (D5) can be maximized independently from the three first ones. We proceed in two steps: first we maximize $\prod_{i, z_{it}=0} f_{y^r|z}(y_{it+1} | z_{it} = 0)$ using OLS; second we maximize $\prod_{i, z_{it}=0} f_{a^r|y^r, z}(a_{it+1} | y_{it+1}, z_{it} = 0)$ using PROBIT.

Now, from equations (5), (6) and (10), the last three terms in the likelihood (D5) are given by:

$$\begin{aligned} f_{z, y^*, a^*}(z_{it} = 1, y_{it+1}, a_{it+1}) &= \Phi\left(\frac{y_{it+1} - x'_{it}\alpha_z - \gamma_z y_{it} - \delta_z a_{it} - \delta_z^* a_{it+1}}{\sigma_z}\right) \times \frac{1}{\sigma_y^*} \phi\left(\frac{y_{it+1} - x'_{it}\alpha_y^* - \beta_y^* \theta_1}{\sigma_y^*}\right) \\ &\quad \times \Phi\left(\frac{(\beta_{1a}^* - \frac{\rho_{ya}^*}{\sigma_y^*} \beta_y^*) \theta_1 + (\alpha_{1a}^* - \frac{\rho_{ya}^*}{\sigma_y^*} \alpha_y^*) x'_{it} + \beta_{2a}^* \theta_2 + \frac{\rho_{ya}^*}{\sigma_y^*} y_{it+1}}{\sqrt{1 - (\rho_{ya}^*)^2}} (-1)^{a_{it+1}-1}\right), \end{aligned}$$

and:

$$\begin{aligned} f_z(z_{it} = 0) &= \Phi_2\left(-x'_{it}\alpha_a^* - \beta_{1a}^* \theta_1 - \beta_{2a}^* \theta_2, \frac{-\beta_y^* \theta_1 + x'_{it}(\alpha_z - \alpha_y^*) + \gamma_z y_{it} + \delta_z a_{it}}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}}, \frac{\rho_{ya}^* \sigma_y^*}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}}\right) \\ &\quad + \Phi_2\left(x'_{it}\alpha_a^* + \beta_{1a}^* \theta_1 + \beta_{2a}^* \theta_2, \frac{-\beta_y^* \theta_1 + x'_{it}(\alpha_z - \alpha_y^*) + \gamma_z y_{it} + \delta_z a_{it} + \delta_z^*}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}}, \frac{-\rho_{ya}^* \sigma_y^*}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}}\right), \end{aligned}$$

where $\phi(\cdot)$ (resp. $\Phi(\cdot)$) is the standard normal PDF (resp. CDF) and $\Phi_2(\cdot, \cdot; \rho)$ is the CDF of the bivariate normal distribution with unit variance and correlation ρ .

Estimation of this part of the likelihood is numerically tedious. Note that this likelihood (weighted by the posterior probabilities) is maximized at each M-step of the EM algorithm. Therefore, it is sufficient to have proper initial conditions for the first maximization. Thereafter, we simply use the part of $(\Theta_1^{(s)}, \Theta_2^{(s)})$ corresponding to the censored regression model as an initial condition for the maximization of the likelihood.

To find initial conditions in the first M-step of the algorithm, we estimated a heckman-type selection model where the wage is the only endogeneous regressor in job mobility decisions. We completed these estimates by plugging as initial conditions for amenity offers the parameter estimates of a PROBIT regression of amenity levels on covariates for job movers.

E Robustness Checks

In this section of the Appendix, we analyze three potential reasons for which estimates of σ_z (heterogeneity in mobility decisions) could be overstated. In this version of the paper, we

only report estimates of some parameters. The tables are available upon request.

E.1 Local maxima of the likelihood

In some cases, the likelihood of the selection model presents two local maxima, one of which corresponding to significantly lower σ_z estimates than the ones reported in Tables 7a-7c. What is the economic relevance of both maxima ?

To address this issue, we varied the number of groups of “productive” and “subjective” heterogeneity and studied the impact on parameter estimates. We focus in this subsection on the estimates for France and the amenity “type of work”. The results are similar for other amenities, and for the Netherlands. In Denmark, in most cases (except in the homogeneous case) the likelihood presents only one maximum.

In the case where K_1 is less than 3, the likelihood presents two local maxima. The first one (denoted as “L”) presents a low σ_z (around .18 with a standard error of .01 for all K_1, K_2) together with a high σ_y^* (from 1.0 in the homogeneous case to .55 in the case $K_1 = 3, K_2 = 2$, where all estimates are highly significant). Thus, in this configuration, the heterogeneity in mobility behavior is mainly accounted for by the variation in wage offers. However the variance of the wage offer distribution implied by the estimates is unrealistically high. For instance, in the homogeneous case, the wage offer variance is almost four times as large as in cross-section.

The second maximum (denoted as “H”) features a wage offer distribution much closer to what is observed in cross-section (σ_y^* is twice as small as at the “L” maximum), yet with much higher estimates for σ_z (e.g. 1.85 for $K_1 = K_2 = 2$, highly significant). In this configuration, the wage explains little of the quit decision, and job-to-job mobility is mostly left unexplained.

Varying the number of groups, one observed that adding heterogeneity to the model shifts the global maximum of the likelihood from the “L” to the “H” configuration. In France for the amenity “type of work”, in the homogeneous case $K_1 = K_2 = 1$ the maximum corresponding to a low σ_z is global. Incorporating more heterogeneity ($K_1 = 2, 3, K_2 = 2$), the maximum of the “H” type becomes higher than the “L” one. Lastly, there is one unique (“H”) maximum for $K_1 = 4$.

We interpret this feature of the likelihood as stemming from exclusion restriction (17). As emphasized in Table 6, the wage at the current job y_1 plays a bigger role, the more precisely unobserved heterogeneity is modeled. For this reason, we think that the maximum of the “L” type is essentially driven by functional forms assumptions (*i.e.* normality), while the maximum of the “H” type is semi-parametrically identified by exclusion restriction (17), which makes sense when unobserved heterogeneity is accounted for.

To confirm this insight in an informal manner, we checked that the sets of parameters corresponding to the two local maxima have rather different implications on the elasticity of the job change probability with respect to the current wage y_t . In the case of the low- σ_z maximum (“L”), the predicted elasticity is high and almost independent of the way unobserved heterogeneity is accounted for. On the contrary, in the high- σ_z (“H”) case, the predicted

elasticity is lower and varies substantially with the number of groups of heterogeneity. We compared the predicted elasticity to the actual one, computed semi-parametrically using Bayes' rule. The fit is quite satisfying in the "H" case, but much worse in the "L" case. This suggests that the elasticity with respect to y_t has very little identifying power in this case. Moreover, as explained in 4.1, this elasticity is at the core of the semi-parametric identification of the selection model, (see equation (19)). For this reason, the identification of the two maxima is likely to come from two different sources, and to be driven by parametric assumptions in the "L" case.

Note that this informal argument also rules out the concern about job offers arrival rates, at least when this rate is homogeneous within groups (θ_1, θ_2) . In our model, job offers are drawn each period. In the context of search models identified from structural restrictions, this can be a problematic assumption as emphasized in Appendix C of Flinn and Heckman (1982). However, in our case, parameters are semi-parametrically identified through exclusion restrictions. Assuming that offers arrive at rate $\lambda > 0$ has no effect on (19), so that the above informal test still holds true in this case.

E.2 Observed heterogeneity: age and gender

It could be that men and women, or older and younger workers, have very different mobility behaviors. In this case, σ_z estimates would be driven by our parametric assumptions about gender and age. We estimated the model separately for men and women, and for workers aged more or less than 35. Interestingly, the parameter estimates are similar for men and women. Estimates for γ_z are slightly lower for men (.48, with a standard error of .10) than for women (.51, with a standard error of .13). Estimates of the amenity parameters in the reservation wages are slightly higher for men: δ_z is .53 (.12) for men, .53 (.16) for women, and δ_z^* is $-.57$ (.15) for men, $-.49$ (.18) for women. Both the current wage and amenity have a slightly stronger (negative) effect on voluntary job change for men. We also note that mobility decisions are slightly more heterogeneous for women: the estimates of σ_z are 1.06 (.21) and 1.20 (.36) for men and women, respectively.

Estimates are also close for "younger" and "older" workers. First, older workers seem more homogeneous in terms of mobility decisions: σ_z estimates are 1.29 (.29) and .87 (.19) for younger and older workers, respectively. Second, the wage has a (slightly) higher explanatory power on the job change variable: γ_z is .56 (.09) *versus* .49 (.13). Lastly, the negative effect of current amenity, relative to the wage, is quite stronger for younger workers: δ_z is .63 (.15) *versus* .35 (.09). Estimates of the δ_z^* parameter are very close.

Splitting the sample into different subgroups and estimating the model on these subsamples never resulted in significantly lower σ_z . The same conclusion was reached after including interaction terms (*e.g.* age \times amenity, gender \times wage...) in the selection part of the model. In other words, in all the cases we considered, the wage and amenity always explained little of job mobility.

E.3 Measurement error

Measurement error is a pervasive issue in applied studies based on interview surveys. Correcting for it is out of the scope of this paper. Instead, we test the sensitivity of our results to (quite substantial) modifications of the data. To this end, we consider the following change in wages:

$$y_{it}^m \equiv y_{it} + \eta\sigma_y\epsilon_{it},$$

where y_{it} are wages reported in the ECHP with standard deviation σ_y , η is a scalar and ϵ_{it} is *i.i.d.*, uncorrelated with y_{it} , and follows the standard normal distribution. We take $\eta = 20\%$, which is close to magnitudes of measurement error reported in the literature. We then estimate the model on the new data, including modified wages y_{it}^m .

The results do not differ substantially from the ones in Tables 7a-7c. For instance, in Denmark for the amenity “type of work” γ_z is slightly lower (.44, with a standard error of .16) and δ_z , δ_z^* are higher (.63 and $-.92$ with standard errors of .22 and .33, respectively) compared to the estimates reported in Tables 7a-7c. As the modification only affects the wage data, the role of amenities in the mobility decision is slightly increased relative to the wage. Yet, the effects of both characteristics are qualitatively similar as in Tables 7a-7c. The influence of measurement error shows more strongly in the σ_z estimate, which increases to 1.47, with a standard error of .47. This can be compared to the estimate in Table 7a, which equals .83 (with a standard error of .18).

As well as the wage, voluntary mobility is likely to be measured with error. For instance, short (within-year) unemployment spells followed by a job change could erroneously be interpreted as “voluntary” by the respondent. Similarly, it is difficult to distinguish genuine job changes from promotions. Part of the transitions classified as “voluntary job changes” in this paper may thus be promotions, ruled by a different process than the one modeled here. To assess the consequences of the mobility variable measured with error, we re-estimate the model substituting $z_{it} + c_{it}$ for z_{it} ; we thus consider all job-to-job transitions to be voluntary. Here we comment on the parameter estimates in the Netherlands, for the amenity “type of work”. The estimates are quite similar to the values reported in Table 7c; yet, several differences in the reservation wage parameters are worth noting. For instance, γ_z is estimated as 1.11 (.07) and δ_z as .55 (.09). Noticeably, δ_z^* is no more significant: $-.06$ (.07). Moreover, the σ_z estimate is higher than in Table 7c: 1.70 (.23). We draw two conclusions from these results. First, the differences between the two sets of estimates justifies the use of *voluntary* mobility in order to assess the role of the wage and amenities on job change. Second, the rise of the estimate of σ_z with a broader definition of job mobility is consistent with the interpretation of this parameter as reflecting the heterogeneity in mobility decisions (which increases when we allow for transitions that are, at least in part, not chosen by the individuals).

F Details of the Computations in Section 6

Let us define, for $a = 0, 1$:

$$\mathbb{E}_z(a) = \mathbb{E}(u_{y_{t+1}}^* | a_{t+1}^* = a, z_t = 1, \tilde{x}_t, \theta_t),$$

To compute $\mathbb{E}_z(a)$, write $\frac{u_{y_{t+1}}^*}{\sigma_y^*} = \rho_1 u_{at+1}^* + \rho_2 \frac{u_{y_{t+1}}^* - u_{zt}}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}} + \eta_t$, where η_t independent of u_{at+1}^* and $(u_{y_{t+1}}^* - u_{zt})$. Hence:

$$\begin{aligned} \rho_{ya}^* &= \rho_1 + \rho_2 \rho_{ya}^* \frac{\sigma_y^*}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}}, \\ \sigma_y^* &= \rho_1 \rho_{ya}^* \sigma_y^* + \rho_2 \sqrt{(\sigma_y^*)^2 + \sigma_z^2}, \end{aligned}$$

which yields expressions for ρ_1 and ρ_2 , since $(\sigma_y^*)^2 + \sigma_z^2 \neq \rho_{ya}^* (\sigma_y^*)^2$. Now, Rosenbaum's computation of the first moments of truncated binormal distributions applies (see *e.g.* Maddala, 1983). Let us denote as:

$$\begin{aligned} A &= -(x'_t \alpha_a^* + \beta_{1a}^* \theta_1 + \beta_{2a}^* \theta_2), \\ B &= \frac{x'_{it} (\alpha_z - \alpha_y^*) - \beta_y^* \theta_1 + \gamma_z y_t + \delta_z a_t + \delta_z^* a_{t+1}^*}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}}. \end{aligned}$$

Then:

$$\begin{aligned} \mathbb{E}_z(1) &= \mathbb{E}(u_{y_{t+1}}^* | u_{at+1}^* > -(x'_t \alpha_a^* + \beta_{1a}^* \theta_1 + \beta_{2a}^* \theta_2), \\ &\quad u_{y_{t+1}}^* - u_{zt} > x'_{it} (\alpha_z - \alpha_y^*) - \beta_y^* \theta_1 + \gamma_z y_t + \delta_z a_t + \delta_z^* a_{t+1}^*, \tilde{x}_t, \theta), \\ &= \sigma_y^* \mathbb{E} \left(\frac{u_{y_{t+1}}^*}{\sigma_y^*} | u_{at+1}^* > A, \frac{u_{y_{t+1}}^* - u_{zt}}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}} > B, \tilde{x}_t, \theta \right), \\ &= \frac{\sigma_y^*}{\Phi_2(-A, -B; \rho)} \left[\rho_1 \left(\phi(A) \Phi \left(\frac{\rho A - B}{\sqrt{1 - \rho^2}} \right) + \rho \phi(B) \Phi \left(\frac{\rho B - A}{\sqrt{1 - \rho^2}} \right) \right) \right. \\ &\quad \left. + \rho_2 \left(\phi(B) \Phi \left(\frac{\rho B - A}{\sqrt{1 - \rho^2}} \right) + \rho \phi(A) \Phi \left(\frac{\rho A - B}{\sqrt{1 - \rho^2}} \right) \right) \right], \\ &= \left[\frac{(\sigma_y^*)^2}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}} \frac{\phi}{\Phi}(-B) \right] \\ &\quad + \left\{ \frac{\sigma_y^*}{\Phi_2(-A, -B; \rho)} \left[\rho_1 \left(\phi(A) \Phi \left(\frac{\rho A - B}{\sqrt{1 - \rho^2}} \right) + \rho \phi(B) \Phi \left(\frac{\rho B - A}{\sqrt{1 - \rho^2}} \right) \right) \right. \right. \\ &\quad \left. \left. + \rho_2 \left(\phi(B) \Phi \left(\frac{\rho B - A}{\sqrt{1 - \rho^2}} \right) + \rho \phi(A) \Phi \left(\frac{\rho A - B}{\sqrt{1 - \rho^2}} \right) \right) \right] - \frac{(\sigma_y^*)^2}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}} \frac{\phi}{\Phi}(-B) \right\}, \\ &\equiv E_z^z(1) + E_z^p(1), \end{aligned}$$

where $\rho = \rho_{ya}^* \frac{\sigma_z}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}}$ is the correlation between u_{at+1}^* and $u_{yt+1}^* - u_{zt}$. Similarly:

$$\begin{aligned}
\mathbb{E}_z(0) &= \mathbb{E}(u_{yt+1}^* | u_{at+1}^* \leq -(x_t' \alpha_a^* + \beta_{1a}^* \theta_1 + \beta_{2a}^* \theta_2), \\
&\quad u_{yt+1}^* - u_{zt} > x_t' (\alpha_z - \alpha_y^*) - \beta_y^* \theta_1 + \gamma_z y_t + \delta_z a_t + \delta_z^*, \tilde{x}_t, \theta), \\
&= \sigma_y^* \mathbb{E} \left(\frac{u_{yt+1}^*}{\sigma_y^*} | u_{at+1}^* \leq A, \frac{u_{yt+1}^* - u_{zt}}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}} > B, x_t, \theta \right), \\
&= \frac{\sigma_y^*}{\Phi_2(A, -B; -\rho)} \left[-\rho_1 \left(\phi(A) \Phi \left(\frac{\rho A - B}{\sqrt{1 - \rho^2}} \right) - \rho \phi(B) \Phi \left(\frac{A - \rho B}{\sqrt{1 - \rho^2}} \right) \right) \right. \\
&\quad \left. + \rho_2 \left(\phi(B) \Phi \left(\frac{A - \rho B}{\sqrt{1 - \rho^2}} \right) - \rho \phi(A) \Phi \left(\frac{\rho A - B}{\sqrt{1 - \rho^2}} \right) \right) \right], \\
&= \left[\frac{(\sigma_y^*)^2}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}} \frac{\phi}{\Phi}(-B) \right] \\
&\quad + \left\{ \frac{\sigma_y^*}{\Phi_2(A, -B; -\rho)} \left[-\rho_1 \left(\phi(A) \Phi \left(\frac{\rho A - B}{\sqrt{1 - \rho^2}} \right) - \rho \phi(B) \Phi \left(\frac{A - \rho B}{\sqrt{1 - \rho^2}} \right) \right) \right. \right. \\
&\quad \left. \left. + \rho_2 \left(\phi(B) \Phi \left(\frac{A - \rho B}{\sqrt{1 - \rho^2}} \right) - \rho \phi(A) \Phi \left(\frac{\rho A - B}{\sqrt{1 - \rho^2}} \right) \right) \right] - \frac{(\sigma_y^*)^2}{\sqrt{(\sigma_y^*)^2 + \sigma_z^2}} \frac{\phi}{\Phi}(-B) \right\}, \\
&\equiv E_z^z(0) + E_z^\rho(0).
\end{aligned}$$

Then, clearly, $\Delta_z^z = \mathbb{E}_z^z(1) - \mathbb{E}_z^z(0)$. We lastly define: $\Delta_z^\rho = \mathbb{E}_z^\rho(1) - \mathbb{E}_z^\rho(0)$.

Table 1: Reason for stopping in previous job

1	obtained better / more suitable job	7	looking after old, sick, disabled persons
2	obliged to stop by employer	8	partner's job required move to another place
3	end of contract / temporary job	9	study, national service
4	sale/closure of own or family business	10	own illness or disability
5	marriage	11	wanted to retire or live off private means
6	child birth / need to look after children	12	other

Table 2: Sample description

Country	DNK	FRA	NLD
individuals	4 010	7 798	6 492
observations	20 023	42 520	31 889
Number of transitions : in % of all obs.			
- unemployment-to-job	1 148 5.7%	1 645 4.6%	1 405 4.4%
- job-to-unemployment	1 134 5.7%	2 215 6.2%	1 321 4.1%
- stay in same job	13 064 65.2%	24 237 68.1%	21 534 67.5%
- job-to-job	2 058 10.3%	1 429 4.0%	2 293 7.2%
- voluntary job-to-job	849 4.2%	603 1.7%	985 3.1%
- constrained job-to-job	1 209 6%	826 2.3%	1 308 4.1%
% of wage increases among:			
- vol. j-t-j transitions	61.2%	60.5%	73.5%
- constr. j-t-j transitions	51.4%	53.2%	64.8%
- stay in same job	47.2%	54.5%	60.0%

Table 3a: Transition matrices $\begin{pmatrix} \mathbb{P}(0,0) & \mathbb{P}(0,1) \\ \mathbb{P}(1,0) & \mathbb{P}(1,1) \end{pmatrix}$ for voluntary job-to-job mobility

Amenities	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
DNK	$\begin{pmatrix} .13 & .28 \\ .09 & .50 \end{pmatrix}$	$\begin{pmatrix} .16 & .25 \\ .16 & .43 \end{pmatrix}$	$\begin{pmatrix} .12 & .20 \\ .16 & .52 \end{pmatrix}$	$\begin{pmatrix} .15 & .22 \\ .19 & .44 \end{pmatrix}$	$\begin{pmatrix} .19 & .19 \\ .20 & .42 \end{pmatrix}$	$\begin{pmatrix} .16 & .19 \\ .16 & .49 \end{pmatrix}$
FRA	$\begin{pmatrix} .13 & .25 \\ .11 & .51 \end{pmatrix}$	$\begin{pmatrix} .25 & .28 \\ .12 & .35 \end{pmatrix}$	$\begin{pmatrix} .32 & .29 \\ .14 & .25 \end{pmatrix}$.	$\begin{pmatrix} .22 & .23 \\ .18 & .37 \end{pmatrix}$	$\begin{pmatrix} .32 & .26 \\ .14 & .28 \end{pmatrix}$
NLD	$\begin{pmatrix} .11 & .31 \\ .10 & .48 \end{pmatrix}$	$\begin{pmatrix} .24 & .30 \\ .15 & .31 \end{pmatrix}$	$\begin{pmatrix} .14 & .21 \\ .14 & .51 \end{pmatrix}$	$\begin{pmatrix} .21 & .25 \\ .15 & .39 \end{pmatrix}$	$\begin{pmatrix} .20 & .18 \\ .21 & .41 \end{pmatrix}$	$\begin{pmatrix} .16 & .21 \\ .14 & .49 \end{pmatrix}$

Table 3b: Transition matrices $\begin{pmatrix} \mathbb{P}(0,0) & \mathbb{P}(0,1) \\ \mathbb{P}(1,0) & \mathbb{P}(1,1) \end{pmatrix}$ for constrained job-to-job mobility

Amenities	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
DNK	$\begin{pmatrix} .16 & .21 \\ .18 & .45 \end{pmatrix}$	$\begin{pmatrix} .19 & .20 \\ .17 & .44 \end{pmatrix}$	$\begin{pmatrix} .13 & .17 \\ .17 & .53 \end{pmatrix}$	$\begin{pmatrix} .12 & .19 \\ .17 & .52 \end{pmatrix}$	$\begin{pmatrix} .19 & .19 \\ .20 & .42 \end{pmatrix}$	$\begin{pmatrix} .27 & .20 \\ .17 & .36 \end{pmatrix}$
FRA	$\begin{pmatrix} .17 & .22 \\ .18 & .43 \end{pmatrix}$	$\begin{pmatrix} .26 & .27 \\ .18 & .29 \end{pmatrix}$	$\begin{pmatrix} .30 & .23 \\ .19 & .28 \end{pmatrix}$.	$\begin{pmatrix} .25 & .20 \\ .17 & .38 \end{pmatrix}$	$\begin{pmatrix} .53 & .23 \\ .13 & .11 \end{pmatrix}$
NLD	$\begin{pmatrix} .16 & .25 \\ .16 & .43 \end{pmatrix}$	$\begin{pmatrix} .27 & .28 \\ .16 & .29 \end{pmatrix}$	$\begin{pmatrix} .13 & .20 \\ .17 & .50 \end{pmatrix}$	$\begin{pmatrix} .18 & .22 \\ .18 & .42 \end{pmatrix}$	$\begin{pmatrix} .15 & .19 \\ .18 & .48 \end{pmatrix}$	$\begin{pmatrix} .32 & .24 \\ .15 & .29 \end{pmatrix}$

Table 3c: Transition matrices $\begin{pmatrix} \mathbb{P}(0,0) & \mathbb{P}(0,1) \\ \mathbb{P}(1,0) & \mathbb{P}(1,1) \end{pmatrix}$ conditional on staying in the same job

Amenities	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
DNK	$\begin{pmatrix} .17 & .10 \\ .13 & .60 \end{pmatrix}$	$\begin{pmatrix} .20 & .13 \\ .14 & .53 \end{pmatrix}$	$\begin{pmatrix} .14 & .10 \\ .10 & .66 \end{pmatrix}$	$\begin{pmatrix} .19 & .12 \\ .13 & .56 \end{pmatrix}$	$\begin{pmatrix} .21 & .07 \\ .08 & .64 \end{pmatrix}$	$\begin{pmatrix} .15 & .12 \\ .11 & .62 \end{pmatrix}$
FRA	$\begin{pmatrix} .20 & .12 \\ .13 & .55 \end{pmatrix}$	$\begin{pmatrix} .36 & .14 \\ .16 & .34 \end{pmatrix}$	$\begin{pmatrix} .32 & .14 \\ .15 & .39 \end{pmatrix}$.	$\begin{pmatrix} .25 & .10 \\ .11 & .54 \end{pmatrix}$	$\begin{pmatrix} .31 & .13 \\ .12 & .44 \end{pmatrix}$
NLD	$\begin{pmatrix} .16 & .11 \\ .13 & .60 \end{pmatrix}$	$\begin{pmatrix} .35 & .14 \\ .17 & .34 \end{pmatrix}$	$\begin{pmatrix} .17 & .12 \\ .12 & .59 \end{pmatrix}$	$\begin{pmatrix} .25 & .13 \\ .15 & .47 \end{pmatrix}$	$\begin{pmatrix} .24 & .07 \\ .08 & .61 \end{pmatrix}$	$\begin{pmatrix} .19 & .13 \\ .11 & .57 \end{pmatrix}$

Table 4: Wage and amenity regressions (DNK,TYPEW)

	wage		amenity		
age	.062 (.002)	.075 (.001)	-.033 (.009)	-.027 (.009)	.0015 (.01)
age ²	-.0007 (.00002)	-.0008 (.00001)	.0005 (.0001)	.0004 (.0001)	.00007 (.0001)
married	-.0095 (.006)	-.0057 (.003)	.13 (.03)	.12 (.03)	.025 (.03)
kid	.034 (.006)	.007 (.003)	.03 (.03)	.023 (.03)	-.017 (.03)
sex	-.22 (.005)	-.039 (.003)	-.038 (.02)	-.00004 (.02)	-.033 (.03)
$\theta_1 = 1$	-	-.98 (.006)	-	-.18 (.06)	-.18 (.07)
$\theta_1 = 2$	-	-.61 (.005)	-	-.24 (.05)	-.37 (.05)
$\theta_1 = 3$	-	-.35 (.005)	-	-.15 (.04)	-.19 (.05)
$\theta_2 = 1$	-	-	-	-	1.73 (.03)
constant	8.2 (.04)	8.2 (.02)	.99 (.18)	1.0 (.2)	-.40 (.2)
R ²	.23	.77	.01	.01	.29

Table 5: Education and gender among unobserved heterogeneity (DNK,TYPEW)

	$\mathbb{P}(\theta)$	Education			Gender	
		3 rd level	2 nd level	<2 nd level	male	female
$\theta_1 = 1$.10	.17	.48	.35	.18	.82
$\theta_1 = 2$.44	.27	.53	.20	.42	.58
$\theta_1 = 3$.37	.44	.45	.11	.64	.36
$\theta_1 = 4$.09	.66	.29	.05	.89	.11
$\theta_2 = 1$.67	.37	.46	.17	.51	.49
$\theta_2 = 2$.33	.34	.49	.17	.54	.46

Table 6: PROBIT of voluntary mobility on observed and unobserved heterogeneity (DNK,TYPEW)

Heterogeneity	No	θ_1	(θ_1, θ_2)
age	.024 (.02)	.086 (.02)	.091 (.02)
age ²	-.00081 (.0002)	-.0015 (.0002)	-.0016 (.0002)
married	-.025 (.04)	-.030 (.04)	-.043 (.04)
kid	-.0597 (.04)	-.051 (.04)	-.057 (.04)
sex	-.12 (.04)	-.089 (.04)	-.090 (.04)
y_t	.19 (.07)	-.52 (.1)	-.53 (.1)
a_t	-.28 (.04)	-.28 (.04)	-.48 (.04)
$\theta_1 = 1$	-	-1.07 (.1)	-1.10 (.1)
$\theta_1 = 2$	-	-.62 (.09)	-.65 (.09)
$\theta_1 = 3$	-	-.33 (.07)	-.35 (.07)
$\theta_2 = 1$	-	-	.37 (.05)
constant	-2.52 (.6)	3.08 (.9)	3.01 (.9)
R ²	.08	.09	.10

Table 7a: ML estimates for the censored regression model - Denmark

	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
<i>Wage offers</i>						
$\alpha_y^*(age)$.067 (.005)	.065 (.005)	.063 (.005)	.065 (.005)	.064 (.005)	.065 (.005)
$\alpha_y^*(age^2)$	-.00078 (.00006)	-.00076 (.00006)	-.00073 (.00006)	-.00075 (.00006)	-.00074 (.00006)	-.00076 (.00006)
$\beta_y^*(\theta_1 = 1)$	-1.04 (.05)	-1.05 (.05)	-1.04 (.05)	-1.05 (.05)	-1.01 (.04)	-1.05 (.05)
$\beta_y^*(\theta_1 = 2)$	-.64 (.02)	-.64 (.02)	-.64 (.02)	-.64 (.02)	-.62 (.02)	-.64 (.02)
$\beta_y^*(\theta_1 = 3)$	-.35 (.02)	-.35 (.02)	-.35 (.02)	-.35 (.02)	-.34 (.02)	-.35 (.02)
$\alpha_y^*(intercept)$	8.33 (.09)	8.35 (.09)	8.38 (.09)	8.35 (.08)	8.37 (.09)	8.35 (.09)
$1/\sigma_y^*$	6.12 (.2)	6.07 (.22)	6.06 (.2)	6.07 (.2)	6.08 (.2)	6.06 (.2)
<i>Amenity offers</i>						
$\alpha_a^*(age)$.038 (.05)	-.046 (.04)	.031 (.04)	-.13 (.04)	.040 (.04)	-.028 (.04)
$\alpha_a^*(age^2)$	-.00027 (.0006)	.00091 (.0005)	-.00014 (.0005)	.0018 (.0005)	-.00041 (.0005)	.00038 (.0005)
$\beta_{1a}^*(\theta_1 = 1)$	-.50 (.2)	.42 (.3)	-.54 (.3)	.66 (.3)	1.19 (.2)	-.50 (.2)
$\beta_{1a}^*(\theta_1 = 2)$	-.36 (.1)	-.087 (.1)	-.30 (.1)	.59 (.1)	.98 (.1)	-.26 (.1)
$\beta_{1a}^*(\theta_1 = 3)$	-.22 (.1)	.020 (.1)	-.31 (.1)	.20 (.1)	1.03 (.1)	-.12 (.1)
$\beta_{2a}^*(\theta_2 = 1)$	2.26 (.1)	2.21 (.09)	1.95 (.09)	1.97 (.08)	2.20 (.09)	2.25 (.09)
$\alpha_a^*(intercept)$	-1.64 (.8)	-.28 (.7)	-1.14 (.7)	1.04 (.7)	-2.12 (.7)	.094 (.7)
<i>Mobility decision</i>						
$\alpha_z(age)$	-.016 (.01)	-.017 (.01)	-.019 (.01)	-.022 (.01)	-.025 (.01)	-.016 (.01)
$\alpha_z(age^2)$.00062 (.0002)	.00063 (.0002)	.00064 (.0002)	.00071 (.0002)	.00072 (.0002)	.00061 (.0002)
$\alpha_z(married)$.029 (.03)	.025 (.03)	.026 (.03)	.028 (.03)	.028 (.03)	.015 (.03)
$\alpha_z(kid)$.043 (.03)	.046 (.03)	.053 (.03)	.051 (.03)	.051 (.03)	.051 (.03)
$\alpha_z(sex)$.062 (.03)	.068 (.03)	.067 (.03)	.070 (.03)	.049 (.03)	.053 (.03)
$\alpha_z(intercept)$	4.87 (.5)	5.01 (.5)	4.99 (.5)	5.13 (.5)	4.56 (.5)	4.89 (.5)
σ_z	.83 (.1)	.84 (.1)	.85 (.18)	.88 (.1)	.84 (.1)	.84 (.1)
$\tan(\rho_{y_a}^* \pi/2)$	-.046 (.08)	.0027 (.07)	-.21 (.07)	-.30 (.08)	-.11 (.07)	-.25 (.07)
<i>Wage/ amenity compensation</i>						
γ_z	.56 (.06)	.54 (.06)	.54 (.06)	.55 (.06)	.60 (.06)	.55 (.06)
δ_z	.38 (.06)	.18 (.04)	.15 (.04)	.11 (.04)	.019 (.04)	.12 (.04)
δ_z^*	-.39 (.076)	-.09 (.05)	-.015 (.06)	-.12 (.05)	.25 (.07)	.088 (.05)

Table 7b: ML estimates for the censored regression model - France

	TYPEW	COND	WTIME	DIST	SECUR
<i>Wage offers</i>					
$\alpha_y^*(age)$.069 (.008)	.069 (.008)	.069 (.008)	.071 (.008)	.069 (.008)
$\alpha_y^*(age^2)$	-.00071 (.0001)	-.00071 (.0001)	-.00071 (.0001)	-.00073 (.0001)	-.00071 (.0001)
$\beta_y^*(\theta_1 = 1)$	-1.80 (.05)	-1.80 (.05)	-1.80 (.05)	-1.80 (.05)	-1.80 (.05)
$\beta_y^*(\theta_1 = 2)$	-1.07 (.03)	-1.07 (.03)	-1.07 (.03)	-1.07 (.03)	-1.06 (.03)
$\beta_y^*(\theta_1 = 3)$	-.61 (.03)	-.61 (.03)	-.61 (.03)	-.60 (.03)	-.60 (.03)
$\alpha_y^*(intercept)$	8.18 (.1)	8.18 (.1)	8.17 (.1)	8.14 (.1)	8.17 (.1)
$1/\sigma_y^*$	4.66 (.2)	4.66 (.2)	4.66 (.2)	4.66 (.2)	4.66 (.2)
<i>Amenity offers</i>					
$\beta_{1a}^*(\theta_1 = 1)$	-.46 (.2)	.1 (.3)	.10 (.2)	.72 (.2)	-.58 (.3)
$\beta_{1a}^*(\theta_1 = 2)$	-.47 (.2)	-.23 (.2)	.52 (.2)	.45 (.2)	-.38 (.2)
$\beta_{1a}^*(\theta_1 = 3)$	-.31 (.2)	-.37 (.2)	.44 (.2)	.45 (.2)	.32 (.2)
$\beta_{2a}^*(\theta_2 = 1)$	2.22 (.1)	2.46 (.1)	2.05 (.1)	1.71 (.1)	2.46 (.1)
$\alpha_a^*(age)$	-.0039 (.05)	-.029 (.04)	.028 (.05)	-.0013 (.04)	.041 (.05)
$\alpha_a^*(age^2)$.00015 (.0007)	.00030 (.0005)	-.00021 (.0007)	.00025 (.0006)	-.00012 (.0007)
$\alpha_a^*(intercept)$	-.69 (.9)	-.34 (.8)	-1.79 (.90)	-.87 (.8)	-2.19 (.9)
<i>Mobility decision</i>					
$\alpha_z(age)$.15 (.06)	.15 (.06)	.15 (.05)	.16 (.06)	.15 (.05)
$\alpha_z(age^2)$	-.00087 (.0006)	-.00089 (.0006)	-.00087 (.0005)	-.00095 (.0006)	-.00085 (.0005)
$\alpha_z(married)$.22 (.1)	.21 (.1)	.21 (.1)	.24 (.1)	.21 (.1)
$\alpha_z(kid)$	-.072 (.1)	-.090 (.09)	-.052 (.09)	-.072 (.1)	-.050 (.09)
$\alpha_z(sex)$.55 (.2)	.54 (.2)	.53 (.2)	.60 (.2)	.49 (.2)
$\alpha_z(intercept)$.52 (1)	.77 (1.07)	-.068 (1)	-.88 (1.4)	.78 (1.02)
σ_z	2.39 (.7)	2.36 (.6)	2.39 (.6)	2.65 (.8)	2.33 (.6)
$\tan(\rho_{ya}^* \pi/2)$.04 (.09)	-.10 (.08)	-.041 (.08)	-.086 (.08)	.12 (.08)
<i>Wage/ amenity compensation</i>					
γ_z	.91 (.1)	.88 (.1)	.93 (.1)	1.0 (.1)	.84 (.1)
δ_z	.49 (.2)	.47 (.2)	.55 (.2)	.18 (.1)	.36 (.1)
δ_z^*	-.80 (.3)	-.77 (.2)	.13 (.2)	.68 (.3)	.19 (.1)

Table 7c: ML estimates for the censored regression model - The Netherlands

	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
<i>Wage offers</i>						
$\alpha_y^*(age)$.077 (.005)	.077 (.005)	.077 (.005)	.078 (.005)	.077 (.005)	.077 (.005)
$\alpha_y^*(age^2)$	-.00083 (.00007)	-.00083 (.00007)	-.00083 (.00007)	-.00083 (.00007)	-.00083 (.00007)	-.00083 (.00007)
$\beta_y^*(\theta_1 = 1)$	-1.30 (.03)	-1.30 (.03)	-1.30 (.03)	-1.30 (.03)	-1.30 (.03)	-1.30 (.03)
$\beta_y^*(\theta_1 = 2)$	-.78 (.02)	-.78 (.02)	-.78 (.02)	-.78 (.02)	-.78 (.02)	-.78 (.02)
$\beta_y^*(\theta_1 = 3)$	-.42 (.01)	-.42 (.01)	-.42 (.019)	-.42 (.01)	-.42 (.01)	-.42 (.01)
$\alpha_y^*(intercept)$	6.58 (.09)	6.59 (.09)	6.58 (.09)	6.58 (.09)	6.58 (.09)	6.59 (.09)
$1/\sigma_y^*$	5.43 (.1)	5.44 (.1)	5.43 (.1)	5.44 (.1)	5.43 (.1)	5.44 (.1)
<i>Amenity offers</i>						
$\alpha_a^*(age)$.048 (.04)	-.084 (.04)	-.032 (.04)	-.053 (.04)	-.050 (.03)	-.14 (.04)
$\alpha_a^*(age^2)$	-.00065 (.0006)	.00078 (.0005)	.00025 (.0006)	.00044 (.0006)	.00069 (.0005)	.0020 (.0006)
$\beta_{1a}^*(\theta_1 = 1)$.37 (.2)	.54 (.2)	.14 (.2)	1.34 (.2)	.41 (.2)	-.21 (.2)
$\beta_{1a}^*(\theta_1 = 2)$	-.17 (.1)	-.38 (.1)	-.29 (.13)	.80 (.1)	.38 (.1)	-.16 (.1)
$\beta_{1a}^*(\theta_1 = 3)$.026 (.1)	-.085 (.1)	-.12 (.1)	.53 (.1)	.20 (.1)	.025 (.1)
$\beta_{2a}^*(\theta_2 = 1)$	2.31 (.09)	2.09 (.08)	2.25 (.09)	2.22 (.08)	1.44 (.08)	2.22 (.09)
$\alpha_a^*(intercept)$	-1.40 (.8)	1.07 (.6)	.26 (.7)	-.037 (.7)	.46 (.6)	2.09 (.7)
<i>Mobility decision</i>						
$\alpha_z(age)$.029 (.02)	.018 (.02)	.019 (.02)	.022 (.02)	.020 (.02)	.025 (.02)
$\alpha_z(age^2)$.00022 (.0002)	.00032 (.0002)	.00032 (.0002)	.00033 (.0002)	.00038 (.0002)	.00030 (.0002)
$\alpha_z(married)$.14 (.05)	.15 (.04)	.14 (.04)	.15 (.05)	.15 (.05)	.14 (.05)
$\alpha_z(kid)$	-.018 (.04)	-.011 (.04)	-.011 (.04)	-.013 (.04)	.00025 (.05)	-.0083 (.04)
$\alpha_z(sex)$.081 (.04)	.085 (.04)	.079 (.04)	.096 (.04)	.10 (.05)	.083 (.04)
$\alpha_z(intercept)$	2.76 (.5)	2.86 (.5)	2.63 (.4)	2.58 (.5)	2.14 (.5)	2.62 (.5)
σ_z	1.15 (.2)	1.12 (.1)	1.11 (.1)	1.20 (.2)	1.26 (.2)	1.18 (.2)
$\tan(\rho_{y_a}^* \pi/2)$.39 (.08)	-.023 (.06)	.024 (.07)	.046 (.07)	-.24 (.07)	.041 (.07)
<i>Wage/ amenity compensation</i>						
γ_z	.70 (.06)	.71 (.05)	.72 (.05)	.73 (.06)	.77 (.06)	.70 (.06)
δ_z	.45 (.07)	.23 (.05)	.16 (.04)	.24 (.05)	.05 (.05)	.11 (.04)
δ_z^*	-.32 (.08)	-.30 (.07)	-.013 (.06)	-.11 (.06)	.36 (.1)	.15 (.07)

Table 8a: Heterogeneity correlation, MWP and Elasticities - Denmark

<i>“Productive” heterogeneity θ_1</i>						
	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
TYPEW	1	.86	.85	.86	.86	.85
COND	.	1	.86	.86	.86	.86
WTIME	.	.	1	.86	.85	.86
WHOURS	.	.	.	1	.85	.86
DIST	1	.85
SECUR	1

<i>“Subjective” heterogeneity θ_2</i>						
	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
TYPEW	1	.65	.64	.62	.58	.62
COND	.	1	.61	.58	.57	.62
WTIME	.	.	1	.68	.60	.60
WHOURS	.	.	.	1	.57	.59
DIST	1	.58
SECUR	1

<i>Marginal Willingness to Pay</i>						
	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
γ_z	.56 (.06)	.54 (.09)	.54 (.06)	.55 (.06)	.60 (.06)	.55 (.06)
δ_z	.38 (.06)	.18 (.04)	.15 (.04)	.11 (.04)	.02 (.04)	.12 (.04)
$MWP = \delta_z/\gamma_z$.68 (.13)	.33 (.09)	.28 (.08)	.20 (.08)	.03 (.07)	.22 (.08)
$MWP^* = -\delta_z^*$.39 (.07)	.09 (.05)	.02 (.06)	.12 (.05)	-.25 (.07)	-.09 (.05)

<i>Elasticities</i>						
	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
ε_{y^*}	2.85 (1.5)	2.74 (1.4)	2.59 (1.4)	2.64 (1.4)	2.73 (1.5)	2.75 (1.5)
ε_y	-1.65 (1)	-1.53 (.9)	-1.45 (.8)	-1.48 (.9)	-1.67 (1)	-1.53 (.90)
ε_{a^*}	1.12 (.6)	.25 (.2)	.32 (.2)	.052 (.2)	-.69 (.4)	-.24 (.2)
ε_a	-1.09 (.6)	-.49 (.3)	-.28 (.2)	-.39 (.3)	-.055 (.1)	-.32 (.2)
ε_{age}	-.0038 (.004)	-.0038 (.004)	-.0040 (.004)	-.0039 (.004)	-.0035 (.004)	-.0038 (.004)

Table 8b: Heterogeneity correlation, MWP and Elasticities - France

<i>“Productive” heterogeneity θ_1</i>					
	TYPEW	COND	WTIME	DIST	SECUR
TYPEW	1	.94	.94	.94	.94
COND	.	1	.94	.94	.94
WTIME	.	.	1	.94	.94
DIST	.	.	.	1	.94
SECUR	1

<i>“Subjective” heterogeneity θ_2</i>					
	TYPEW	COND	WTIME	DIST	SECUR
TYPEW	1	.68	.62	.58	.63
COND	.	1	.70	.60	.66
WTIME	.	.	1	.61	.65
DIST	.	.	.	1	.58
SECUR	1

<i>Marginal Willingness to Pay</i>					
	TYPEW	COND	WTIME	DIST	SECUR
γ_z	.91 (.1)	.88 (.1)	.93 (.1)	.77 (.06)	.84 (.1)
δ_z	.49 (.2)	.47 (.2)	.55 (.2)	.05 (.05)	.36 (.1)
$MWP = \delta_z/\gamma_z$.54 (.2)	.53 (.2)	.59 (.2)	.06 (.07)	.43 (.1)
$MWP^* = -\delta_z^*$.80 (.3)	.77 (.2)	-.13 (.2)	-.36 (.1)	-.19 (.1)

<i>Elasticities</i>					
	TYPEW	COND	WTIME	DIST	SECUR
ε_{y^*}	1.44 (1.8)	1.35 (1)	1.42 (2.3)	1.44 (2.7)	1.55 (2)
ε_y	-1.33 (1.7)	-1.21 (1)	-1.34 (2.3)	-1.44 (2.7)	-1.32 (1.7)
ε_{a^*}	1.17 (1.6)	1.02 (1)	-.16 (.4)	-.96 (1.7)	-.30 (.5)
ε_a	-.72 (1)	-.63 (.6)	-.77 (1.3)	-.25 (.43)	-.55 (.8)
ε_{age}	-.0013 (.004)	-.0013 (.004)	-.0017 (.003)	-.0013 (.003)	-.0013 (.003)

Table 8c: Heterogeneity correlation, MWP and Elasticities - The Netherlands

<i>“Productive” heterogeneity θ_1</i>						
	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
TYPEW	1	.90	.90	.90	.90	.90
COND	.	1	.90	.90	.90	.90
WTIME	.	.	1	.90	.90	.90
WHOURS	.	.	.	1	.90	.90
DIST	1	.90
SECUR	1

<i>“Subjective” heterogeneity θ_2</i>						
	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
TYPEW	1	.61	.63	.60	.59	.61
COND	.	1	.58	.57	.55	.56
WTIME	.	.	1	.66	.62	.59
WHOURS	.	.	.	1	.58	.56
DIST	1	.57
SECUR	1

<i>Marginal Willingness to Pay</i>						
	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
γ_z	.70 (.06)	.71 (.05)	.72 (.05)	.73 (.06)	.77 (.06)	.70 (.06)
δ_z	.45 (.07)	.23 (.05)	.16 (.04)	.24 (.05)	.05 (.05)	.11 (.04)
$MWP = \delta_z/\gamma_z$.64 (.11)	.32 (.07)	.22 (.06)	.33 (.07)	.06 (.07)	.16 (.06)
$MWP^* = -\delta_z^*$.32 (.08)	.30 (.07)	.01 (.06)	.11 (.06)	-.36 (.10)	-.15 (.07)

<i>Elasticities</i>						
	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
ε_{y^*}	2.16 (1)	2.17 (1)	2.01 (.9)	2.15 (.9)	1.88 (.9)	1.99 (.9)
ε_y	-1.50 (.71)	-1.56 (.7)	-1.49 (.7)	-1.56 (.7)	-1.47 (.7)	-1.41 (.7)
ε_{a^*}	.68 (.4)	.64 (.3)	.23 (.16)	.029 (.1)	-.69 (.4)	-.31 (.2)
ε_a	-.99 (.5)	-.49 (.25)	-.49 (.25)	-.35 (.2)	-.10 (.1)	-.22 (.1)
ε_{age}	-.0032 (.003)	-.0032 (.003)	-.0031 (.003)	-.0031 (.003)	-.0033 (.003)	-.0036 (.003)

Table 9: Wage differentials

	TYPEW	COND	WTIME	WHOURS	DIST	SECUR
Denmark						
Job stayers: Δ	.026 (.017)	.005 (.016)	-.16 (.03)	-.27 (.04)	-.25 (.04)	-.007 (.02)
Job changers:						
“supply” Δ_z^z	-.012 (.0045)	-.0027 (.0018)	-.0035 (.0018)	-.0005 (.05)	.0077 (.003)	.0027 (.002)
“demand” Δ_z^p	-.015 (.034)	.00025 (.02)	-.071 (.03)	-.051 (.027)	-.030 (.04)	-.064 (.03)
France						
Job stayers: Δ	.066 (.01)	.014 (.01)	-.062 (.02)	-	.050 (.01)	.086 (.01)
Job changers:						
“supply” Δ_z^z	-.0079 (.01)	-.0077 (.01)	.0012 (.002)	-	.006 (.02)	.0019 (.003)
“demand” Δ_z^p	.013 (.06)	-.036 (.05)	-.019 (.05)	-	-.04 (.08)	.047 (.04)
The Netherlands						
Job stayers: Δ	.051 (.01)	.010 (.01)	-.049 (.01)	-.17 (.02)	-.058 (.015)	.017 (.01)
Job changers:						
“supply” Δ_z^z	-.0073 (.003)	-.0067 (.003)	-.0023 (.0015)	-.0003 (.002)	.0066 (.003)	.0032 (.002)
“demand” Δ_z^p	.11 (.03)	-.0062 (.02)	.014 (.03)	.0065 (.03)	-.059 (.02)	.010 (.02)

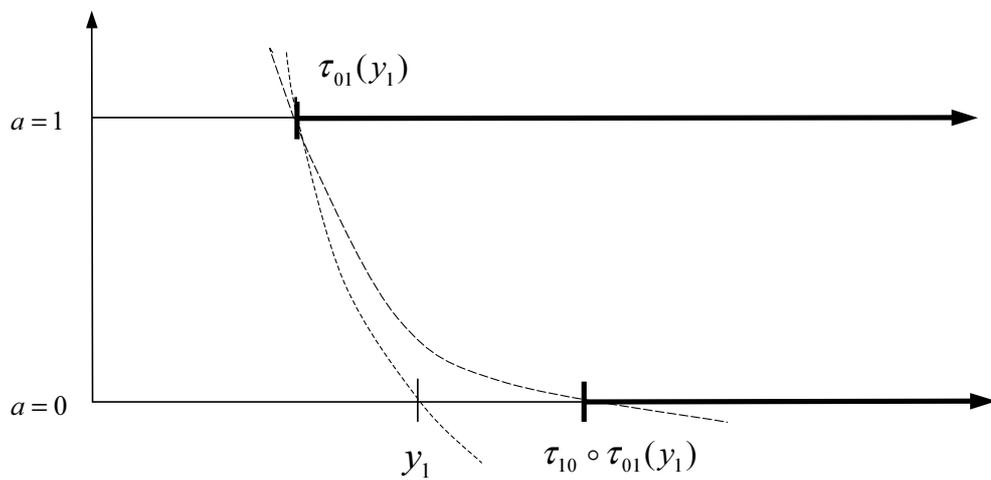


Figure 1: Reservation wages

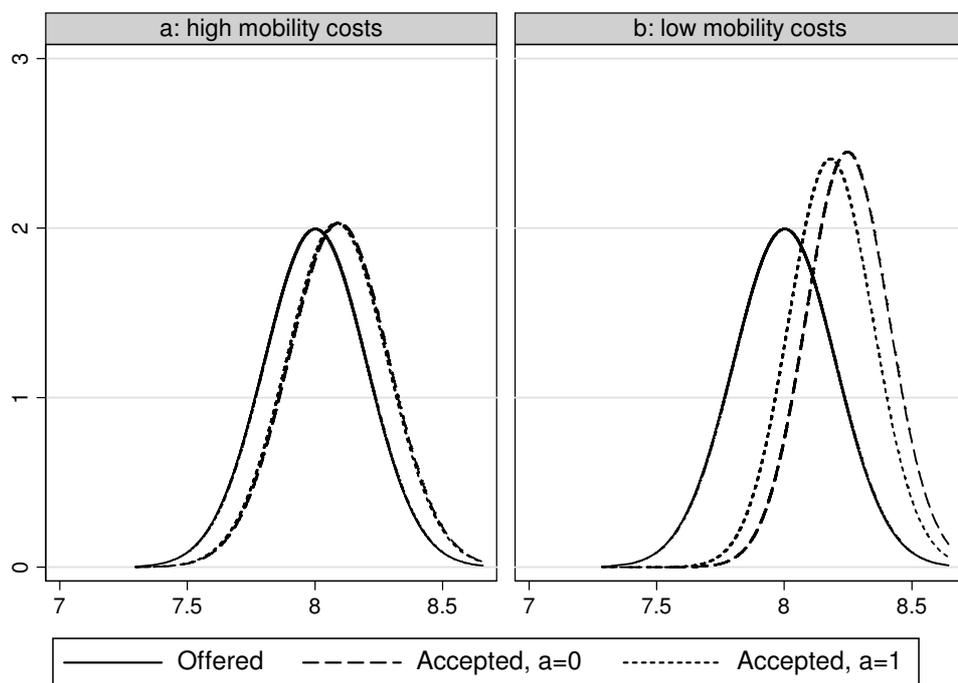


Figure 2: Offered and accepted wage distributions