The Pervasive Absence of Compensating Differentials*

Stéphane Bonhomme† CEMFI, Madrid

Grégory Jolivet‡ University of Bristol

October, 2008

*We thank the editor (John Rust) and two anonymous referees for their recommendations which 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, Edwin Leuven, Thierry Magnac, David Margolis, Costas Meghir, Claudio Michelacci, Jean-Marc Robin, Abla Safir and Gerard van den Berg as well as participants from the COST Conference in Uppsala, the 2005 IZA Summer School, the 12th Panel Data conference in Copenhagen and seminar participants at CEMFI, CREST, Paris-Jourdan, Université de Paris I and Tinbergen Institute for their comments and remarks. Stéphane Bonhomme gratefully acknowledges the financial support from the Spanish Ministry of Science and Innovation through the Consolider-Ingenio 2010 Project "Consolidating Economics", and from the Spanish MEC, Grant SEJ2005-08880. The usual disclaimer applies.

†**Corresponding author:** CEMFI, Casado del Alisal, 5, 28014 Madrid, Spain. E-mail: bonhomme@cemfi.es

‡E-mail: Gregory.Jolivet@bristol.ac.uk

Abstract

We study the relation between individual preferences for job amenities (e.g. type of work, job security) and compensating wage differentials in cross-section. To this end, we estimate a partial equilibrium job search model on panel data from eight European countries. There are five non wage job characteristics and two sources of job-to-job mobility: on-the-job search and reallocation shocks. We also allow for two types of unobserved heterogeneity. We find strong preferences for amenities, especially job security. Yet, these preferences do not translate into significant wage differentials in cross-section. Counterfactual experiments show that one would need extremely low levels of search frictions for compensating differentials to arise. Lastly, a similar exercise on the distribution of job change outcomes reveals the role of constrained job-to-job mobility in the absence of compensating wage differentials.

JEL codes: C33-35, J31-33, J63-64 and J81.

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

1 Introduction

In theory, non wage job characteristics (e.g. type of work, working conditions, job security) are potential determinants of wage dispersion and labor market turnover (see Rosen, 1986). However, very different estimates of workers' Marginal Willingness to Pay (MWP hereafter) for these amenities have been obtained using either cross-sectional data on wages and amenities, or job duration data. Hwang, Mortensen and Reed (1998) build a structural on-the-job search model that provides an explanation for these conflicting results.[1] In this paper, we take a partial equilibrium version of their model to data on European countries.

In a perfectly competitive labor market, there must exist positive wage differentials for disamenities (Smith, 1976). The literature on hedonic models, initiated by Rosen (1974, 1986), provides a relevant theoretical framework for the analysis of these compensating differentials, suggesting to estimate workers' MWP with cross-sectional hedonic wage regressions. However, this method has not yielded strong empirical evidence of compensating differentials. Typical estimates in this literature, starting with Thaler and Rosen (1975), are of small order of magnitude, often less than five percent of the wage, if not insignificantly different from zero or wrong-signed.[2]

The presence of labor market frictions can explain why preferences are not reflected in cross-section. If searching for job offers is costly and subject to incomplete information, hedonic prices and workers' MWP need not coincide. Therefore, low wage/amenity correlations must not be interpreted as reflecting weak preferences for job attributes. Gronberg and Reed (1994) use job duration data in order to estimate workers' MWP. They find large and significant MWP for two non wage attributes– measuring several aspects of working conditions– out of four. Since then, several authors have used their methodology and found MWP estimates of similar orders of magnitude.[3]

To reconcile these two approaches from an empirical perspective, we estimate a partial equilibrium version of the model of Hwang *et al.* (1998). Time is discrete, and workers

[1]Lang and Majumdar (2004) obtain a similar conclusion within a non sequential search framework.

[2]Several studies (Goddeeris, 1988, Kostiuk, 1990, Daniel and Sofer, 1998) have found compensating differentials in some specific cases. Still, the general picture of the literature based on hedonic regressions is rather inconclusive.

[3]See, among others, Van Ommeren et al. (2000) and Dale-Olsen (2006). An early related contribution is Herzog and Schlottmann (1990).

belong to a stationary environment. At each period a job offer arrives with some probability, drawn from an exogenous distribution of wages and amenities. Workers accept every offer yielding more utility, where utility is a linear combination of the (log) wage and amenities. The weight of each attribute in the utility function is the worker's MWP for that amenity. Transitions to employment and non employment also occur with some probability at each period. A difference with Hwang *et al.* (1998) is that we also allow for shocks that exogenously reallocate workers between jobs. Hence, there are two types of job-to-job mobility in the model: voluntary and constrained.

In this type of on-the-job search models, compensating wage differentials may arise because workers select themselves between jobs and may then trade lower (resp. higher) wages for better (resp. worse) amenities. At the steady-state equilibrium, this produces a cross-sectional distribution of wages and amenities among employed workers. Our analysis will focus on the relation that maps individual preferences (MWP for amenities) onto this distribution. The mapping depends on the distribution of job offers, in particular the wage/amenity correlation posted by firms. It also depends on search frictions, measured using an index that counts the average number of outside offers received by employed workers between two adverse shocks (constrained job reallocation or job-to-non employment transition). The lower the search frictions index, the less workers select themselves between jobs, and the greater the difference between wage/amenity correlation in cross-section and workers' MWP for amenities. The main contribution of this paper is to take the relation between workers' preferences for amenities and compensating wage differentials in cross-section to the data, with a special emphasis on the role of search frictions.

We estimate the model on European data from the European Community Household Panel (ECHP) for the years 1994-2001. We study eight countries (Austria, Denmark, Spain, Finland, France, Italy, the Netherlands and Portugal) and allow for five binary amenities. We assume that wage offers are log-normal, and allow for individual covariates (age and education) in wage and amenity offers, as well as in MWP parameters. We also allow for two types of unobserved heterogeneity, that are identified from the panel dimension of the data. The first type reflects workers' productivity, and appears in the wage and amenity equations. Allowing for productive unobserved heterogeneity is important, as shown in Brown (1980) and Hwang *et al.* (1992). The second type of heterogeneity, that we refer to as "subjective", appears only in amenity equations. It is motivated by the nature of the amenity variables we use, which consist of self-reported measures of satisfaction with several dimensions of the job. In line with Duncan and Holmlund (1983), we think that such indicators may suffer from substantial biases, of a more "subjective" nature.

The presence of multiple amenities and two sources of unobserved heterogeneity complicates the estimation. Moreover, as workers' reservation values depend on MWP parameters and job mobility is a zero/one decision, the sample log-likelihood is not continuous in workers' MWP. To circumvent this problem, we develop an iterative estimation algorithm, that we embed into an EM-type estimation procedure in order to deal with unobserved heterogeneity.

We find positive MWP for most job attributes in all countries, job security showing the largest MWP. In contrast, regressing wages on amenities while controlling for observed and unobserved heterogeneity yields small, often insignificant, correlations.

Then, we proceed to a counterfactual experiment, using the estimates from our model and varying the degree of search frictions exogenously. We show that, even if workers had far more opportunities to move across jobs than they actually have, the strong preferences for amenities would only be marginally reflected in cross-section. Hence, wage differentials for amenities would still bear little resemblance with the underlying preferences. This exercise can be seen as an empirical assessment– in a partial equilibrium model– of the point made in a simulation exercise by Hwang *et al.* (1998).

Lastly, as an alternative to the cross-section of wages and amenities earned by employed workers, we look at the wage/amenity outcomes of job changes. We derive the mapping between the preference parameters and this distribution and show that it depends on job offers, on the index of search frictions and also on the ratio of arrival rates of reallocation shocks and outside job offers. Varying this ratio, we show empirically that job change outcomes could yield some evidence of compensating wage differentials if job-to-job mobility was solely voluntary. However, even a small share of constrained transitions makes preferences almost invisible in the wage/amenity distribution of job changers.

A recent contribution by Dey and Flinn (2008), focusing on workers' MWP for health insurance coverage, is closely related to our approach. We depart from this paper on at least three aspects: we allow for two types of job-to-job mobility, we account for five different amenities simultaneously and we study compensating differentials not only in the distribution of employed workers but also on that of job changers.[4] In particular, controlling for a set of five amenities greatly complicates the estimation of MWP and, because of data constraints, leads us to develop a different estimation approach than the one suggested by Dey and Flinn.

The outline of the paper is as follows: section 2 presents the partial equilibrium on-the-job search model and derives the steady-state distribution of wages and amenities. Section 3 presents the data and some descriptive statistics. In section 4, we detail our estimation strategy, and we comment on the parameter estimates in section 5. Section 6 is devoted to the joint analysis of compensating wage differentials in cross-section and search frictions. Lastly, section 7 concludes.

2 A model of wages, amenities and job mobility

We write a partial equilibrium model of workers' wages, amenities, and mobility decisions. The model builds on Hwang *et al.* (1998), and allows for both voluntary and constrained job-to-job transitions.

The environment. Time is discrete. Two types of agents participate in the labor market: firms which post non negotiable job offers and a mass unit of workers. Workers can be employed or not, in either case they search for jobs. In this section, we assume that workers are homogeneous. In the estimation, we will account for both observed and unobserved individual heterogeneity and assume separate labor markets. Jobs are described by a pair (y, a), constant within job, where y is the (logarithm of the) wage and $a = (a_k)_{k=1,\ldots,K}$ is a K-dimensional column vector of non monetary job characteristics, also called amenities. There are two primitives in the model:

- An instantaneous utility function, $u(y, a) = y + \delta' a$.
- A job offer distribution $F(y^*, a^*)$, that we take as given. We denote the pdf as $f(y^*, a^*)$.

Each component δ_k of the vector δ can be directly interpreted as the MWP for the amenity a_k. Note that the existence of $F(y^*, a^*)$ implies that there is a dispersion of wages

[4] However, Dey and Flinn (2008) model labor market decisions of households, arguing that health insurance can be seen as a public good within the household, while our analysis is at the individual level.

and amenities for homogeneous workers.[5]

At each date, employed workers face three types of shocks: *i)* with probability q their job is destroyed and they go back to non employment, *ii)* with probability λ_2, their job is destroyed but they instantaneously get a new offer, and *iii)* with probability λ_1, they receive an outside offer. Non employed workers receive a job offer with probability λ_0 at each date. Workers draw their job offers in F. We assume that no offer is associated with a value lower than that of non employment[6] so that non employed workers and employed workers hit by a reallocation shock, λ_2, accept any offer they receive. In contrast, employed workers receiving an outside offer through a λ_1 shock accept it only if it yields a value greater than the one associated with their current job.

We introduce reallocation shocks, occuring with probability λ_2, in order to allow workers to experience constrained job-to-job transitions. These transitions can result from an employer-provided outplacement program, or from the workers' job search activity during the notice period. In the empirical analysis, these reallocation shocks may also account for short term non employment or, equivalently, for the non stationary process ruling job reaccession (see Shimer, 2005, or Jolivet *et al.*, 2006). We discuss possible interpretations of λ_2 in Appendix A.

Job values and labor turnover. We assume that the discount rate and the value associated with non employment are constant. More importantly, we assume that the search environment does not depend on the current job characteristics, i.e. neither F nor $(\lambda_1, \lambda_2, q, \lambda_0)$ are functions of (y, a). Therefore the value $V(y, a)$ of a job (y, a) is an increasing function of the instantaneous utility $u(y, a)$, and voluntary job changes are equivalently based on job value or on instantaneous utility comparisons.[7]

Formally, if $F_u(u)$ is the probability that an offer yields an instantaneous utility lower than u, we can write the probability that a worker employed at (y, a) leaves this job, voluntarily

[5]Hwang *et al.* (1998) derive the existence of F under two conditions: *i)* firms have different costs of producing amenities, which yields one amenity level per firm; and *ii)* there are search frictions, so that there exists a non degenerate wage distribution for each level of amenity, as in the Burdett and Mortensen (1998) on-the-job search model.

[6]This would be the case in an equilibrium search model as no firm would have any interest in posting an offer that no one would accept.

[7]For this result to hold, and for mobility decisions to allow identification of the structural parameters δ, it is crucial that the search environment does not depend on (y, a). This is a strong assumption, especially for amenities such as job security.

or not, as:[8]

$$\mathbb{P}(\text{leave}|y,a) = q + \lambda_2 + \lambda_1 \overline{F}_u\left(y + \delta' a\right). \tag{1}$$

The first (resp. second) term on the right-hand-side of (1) is the probability that the worker is forced to go to non employment (resp. is reallocated to another job). The last term is the probability to receive an outside offer better than (y, a) through on-the-job search. Equation (1) implies that the probability to leave a job (y, a) is a decreasing function of the instantaneous utility $y + \delta' a$. Job durations can thus be used to identify the MWP δ, which is the main parameter of interest in our model. Using only job hazard rates to identify δ is the approach of Gronberg and Reed (1994).

Steady-state equilibrium. The model also has implications for wages and amenities in cross-section. They follow from deriving the steady-state equations of some stocks of interest.

The flows into and out of the stationary non employment stock U are equal, hence:

$$\lambda_0 U = \delta(1 - U). \tag{2}$$

Then, let $G_u(u)$ denote the probability that a worker is employed in a job yielding an instantaneous utility lower than u. At the steady state, the stock $(1 - U)G_u(u)$ is constant. Using the mobility rule we can write :

$$\left[\delta + \lambda_1 \overline{F}_u(u) + \lambda_2 \overline{F}_u(u)\right](1 - U)G_u(u) = \lambda_0 U F_u(u) + \lambda_2 F_u(u)(1 - U)\overline{G}_u(u),$$

which, using (2), implies:

$$G_u(y + \delta' a) = \frac{F_u(y + \delta' a)}{1 + \kappa \overline{F}_u(y + \delta' a)} \quad \Leftrightarrow \quad g_u(y + \delta' a) = (1 + \kappa) \cdot \frac{f_u(y + \delta' a)}{\left[1 + \kappa \overline{F}_u(y + \delta' a)\right]^2}, \tag{3}$$

where f_u (resp. g_u) is the pdf associated with F_u (resp. G_u), and $\kappa = \lambda_1/(\delta + \lambda_2)$ is the ratio of the arrival rates of positive and adverse shocks. We will interpret κ as an index of labor market frictions, consistently with the on-the-job search literature (e.g., Ridder and Van den Berg, 2003). The larger κ, the more workers receive outside job offers between two adverse shocks (job destruction or job reallocations). Hence, search frictions are all the more stringent for workers as κ is low.

[8]In this paper, we use the notation $\overline{F}_u(x) \equiv 1 - F_u(x)$. The same goes for all the other cdf's.

Now, the model implies that the conditional distribution of wage/amenity offers given utility is equal to the distribution of accepted wages and amenities given utility.[9] Denoting as $f(y, a)$ (resp. $g(y, a)$) the density of wage/amenity pairs among job offers (resp. among employed workers), we thus have:

$$\frac{g(y,a)}{g_u(y+\delta' a)} = \frac{f(y,a)}{f_u(y+\delta' a)}. \tag{4}$$

Taking (3) into (4), we can write the steady-state distribution of wages and amenities conditional on being employed as:

$$g(y,a) = (1+\kappa) \cdot \frac{f(y,a)}{\left[1+\kappa \overline{F}_u(y+\delta' a)\right]^2}. \tag{5}$$

Equation (5) presents the mapping between the preference parameters δ_k and the steady-state cross-sectional distribution of wages and amenities. Clearly, the correlation between wages and amenities in cross-section (i.e. in the G distribution) is a function of three factors. The first one is workers' preferences for amenities, represented by the parameter vector δ. The second factor is the wage/amenity correlation in job offers, that appears in the terms f and F_u. This feature is exogenous in our partial equilibrium model. Search frictions, through the index κ, are the last element likely to affect compensating differentials in cross-section. One goal of this paper is to assess the contribution of these three factors to compensating wage differentials for amenities.

3 Data and descriptive statistics

In this section, we present the data and produce a set of descriptive statistics.

3.1 The ECHP

We use the European Community Household Panel (ECHP). The ECHP is a longitudinal survey of households based on a standardized questionnaire and covering 15 countries from 1994 to 2001. Each individual in a household is interviewed once a year and every individual present in the initial sample is followed over the eight waves, unless attrition occurs.

[9] This point has already been made by Dey and Flinn (2008).

Each observation consists of a set of individual characteristics, such as age and gender, together with standard information on the present job: wage, date of start and, importantly, satisfaction with several non wage job characteristics.

Amenities Among the numerous job characteristics available in the ECHP is a set of job amenities. These variables give the subjective valuation of the worker with a given aspect of his 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:

- TW	:	Type of work
- CD	:	Working conditions
- WT	:	Working times
- DI	:	Distance to job/commuting
- SE	:	Job security

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 clustering is consistent with the literature following Rosen (1986) where amenities take two values: zero for "bad" jobs, one for "good" jobs.[10]

The interpretation of these subjective variables calls for prudence. In the next section, we assume that a worker declares to be satisfied with an amenity if the "objective" amenity (e.g. the distance to one's job, in kilometers) exceeds an individual specific threshold (depending e.g. on whether public transportation is safe or crowded). We let this threshold depend on observable and unobservable characteristics, in order to account for the subjective nature of the data.

Eight countries under study. Even though the ECHP is an actual survey and not a collection of national labor force surveys, some variables (especially amenities) may not be

[10]It 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).

available in every wave and/or country. In particular, the survey only lasts three years in Germany and the United Kingdom. Therefore we restrict our analysis to countries where amenities are available and rarely missing (the non-response rate is less than 1%). In this paper, we focus on Austria, (AUS), Denmark (DNK), Spain (ESP), Finland (FIN), France (FRA), Italy (ITA), the Netherlands (NLD) and Portugal (PRT). These eight countries cover the scope of the different mobility patterns in Europe, from rather static labor markets in some Latin countries (France and Italy) to markets with a high turnover (Denmark).

Individual Characteristics. The model assumes stationarity and separate job markets according to individual characteristics. We introduce two dummies: one indicating whether the individual is strictly more than 35 years old and another indicating whether he has achieved a third level (i.e. college) education. In particular, individual MWP are allowed to vary with age and education.[11] Since we do not model the decision to participate in the labor market or the distinction between full-time and part-time jobs, we restrict our analysis to male workers.

3.2 Sample description

For each country, we construct 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. Thus, a worker present in the eight waves is associated with seven observations, each observation containing his job status (employment status, wage, amenities) and his individual characteristics both at date t and $t+1$. Moreover, for each observation, we have a mobility indicator telling whether the worker stayed in his job, changed job or moved from or to non employment between t and $t+1$. We can thus observe all the individual job or non employment spells. For each job spell, we compute the mean wage and amenities.[12] Lastly, since we do not focus on participation, we cluster unemployment and inactivity, and define employment as paid

[11] Controlling for age in an analysis of compensating differentials is important, as older workers might have different preferences for some job characteristics. However, this might conflict with the stationary assumption in the model. For simplicity, we assume that workers take their current search environment and preferences as stationary when computing their value functions. For instance, workers aged 33 do not take into account that they will no longer draw offers at the same rate and in the same distribution in three years time.

[12] Specifically, we take the mean of the log of monthly wages. Moreover, we average the amenity values on a 1/6 scale on each job spell, and then compute the binary indicators as explained in the previous subsection.

jobs associated with more than 15 hours of work per week. We drop self-employed workers from the sample. Descriptive statistics are shown in Table 1.

Table 1 shows a heterogeneous picture of labor turnover in Europe. At one end of the spectrum, Denmark shows relatively short job spells and a high percentage of job-to-job transitions, while at the other end, France, Italy and Portugal show longer job spells and less job-to-job transitions. Spain is rather atypical, as the short duration of job spells is mostly due to transitions between employment and non employment.

Table 1 about here

Taking a closer look at wages before and after job changes (last row of Table 1) we can see that in each country there is a large share of job changes associated with a wage cut, from 36% in Finland to 46% in Denmark. This can mean that at least part of job-to-job transitions are constrained, or that the wage is not the only job characteristic entering workers' utility function. In order to disentangle these two explanations, we estimate the structural model we presented in Section 2.

4 Estimation

This section is divided into three parts. First, we present the model's specification and derive the individual likelihood. Second, we show how we solve the estimation problem raised by the presence of MWP in employed workers' reservation values. Lastly, we discuss the estimation of the model in the presence of individual heterogeneity.

4.1 The econometric model

Wage and amenity offers. Let x denote observed characteristics of workers and $z = (z_1, z_2)$ their unobserved attributes. Job offers consist of a wage y^* and a vector of amenities $a^* = (a_1^*, ..., a_K^*)$ which are assumed to follow:

$$\begin{aligned} y^* &= \mu_y(x, z_1) + \rho(x)' a^* + \sigma_y u_y, \\ a_k^* &= \mathbf{1}\left\{\mu_{a_k}(x, z_2) + u_{a_k} > 0\right\}, \quad k = 1, ..., K, \end{aligned} \tag{6}$$

where $u_y, u_{a_1}, ..., u_{a_K}$ are independent standard normal, $\mathbf{1}\{\}$ is the indicator function, and (z_1, z_2) follows a bivariate normal distribution. Moreover, μ_y is linear in x, z_1, the average latent amenity μ_{a_k} is linear in x and z_2, and the wage/amenity correlation in job offers $\rho(x)$, which plays an important role in the analysis, is linear in x.

We interpret z_1 as an unobserved productive characteristic. We allow z_1 and z_2 to be correlated, and view z_2 as a mixture of productive and more "subjective" characteristics of the worker. In the model, we interpret each binary amenity indicator entering workers' utiliy as the result of the comparison between a "true" (or objective) amenity and an individual-specific threshold that depends on observed and unobserved characteristics.

The pdf of wage/amenity offers (y^*, a^*) is thus, denoting the standard normal pdf and cdf as ϕ and Φ, respectively:

$$f(y^*, a^*|x, z_1, z_2) = \frac{1}{\sigma_y} \cdot \phi \left[\frac{y^* - \mu_y(x, z_1) - \rho(x)' a^*}{\sigma_y} \right] \cdot \prod_{k=1}^{K} \Phi \left[(\mu_{a_k}(x, z_2)) \cdot (-1)^{1-a_k^*} \right], \quad (7)$$

and the probability of receiving a job associated with a utility greater than u equals:

$$\overline{F}_u(u|x, z_1, z_2) = \sum_{a^* \in \{0,1\}^K} \Phi \left[\frac{\mu_y(x, z_1) + \rho(x)' a^* + \delta(x)' a^* - u}{\sigma_y} \right] \cdot \prod_{k=1}^{K} \Phi \left[(\mu_{a_k}(x, z_2)) \cdot (-1)^{1-a_k^*} \right]. \quad (8)$$

Transition parameters and preferences. We let all transition parameters $\lambda_0(x)$, $\lambda_1(x)$, $\lambda_2(x)$ and $q(x)$ be log-linear functions of observed individual characteristics, and workers' MWP $\delta_1(x), ..., \delta_K(x)$ be linear in x.[13]

Labor turnover. Consider two periods t and $t+1$ and an individual with characteristics (x, z_1, z_2). Let e_t be equal to one if this individual is employed at t and to zero otherwise. If the worker is employed at date t (resp. $t+1$), we denote his wage/amenity pair as (y_t, a_t) (resp. (y_{t+1}, a_{t+1})). Moreover we define the dummies s_t, jj_t, ju_t respectively equal to one if the worker stays in his job, changes job or becomes non employed between t and $t+1$. Likewise, an individual non employed at date t can get a job between t and $t+1$, in which case $uj_t = 1$, or he can stay non employed and then $uu_t = 1$.

Initial conditions. The initial date is denoted as t_0. We use the stationary relations (2) and (3) to model the probability of being employed and earning a given wage/amenity pair

[13]Importantly, we allow MWP parameters to depend on observed heterogeneity, but not on unobserved heterogeneity. Having a third dimension of unobserved individual heterogeneity is an interesting extension that we do not consider here.

at $t = t_0$.

Individual contributions to the likelihood. We can now write the contribution to the likelihood of an individual observed between dates t_0 and T, conditional on observed and unobserved heterogeneity (x, z_1, z_2):

$$\underbrace{f_{t_0}\left(e_0, y_0, a_0|x, z_1, z_2\right)}_{=f_{t_0}} \prod_{t=t_0}^{T-1} \underbrace{f_{t+1}(e_{t+1}, y_{t+1}, a_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t|e_t, y_t, a_t, x, z_1, z_2)}_{=f_{t+1}} \quad , \tag{9}$$

where:

$$f_{t_0} \;=\; \left(\frac{q(x)}{\lambda_0(x)+q(x)}\right)^{1-e_{t_0}} \left(\frac{\lambda_0(x)}{\lambda_0(x)+q(x)}\right)^{e_{t_0}} \left[\frac{[1+\kappa(x)]f\left(y_{t_0}, a_{t_0}|x, z_1, z_2\right)}{\left[1+\kappa(x)\overline{F}_u(y_{t_0}+\delta(x)'a_{t_0}|x, z_1, z_2)\right]^2}\right]^{e_{t_0}},$$

and:

$$\begin{aligned} f_{t+1} \;=\; & [q(x)]^{ju_t}[1-\lambda_0(x)]^{uu_t} \\ \times\; & [\lambda_0(x)]^{uj_t}\left[f\left(y_{t+1}, a_{t+1}|x, z_1, z_2\right)\right]^{uj_t+jj_t} \\ \times\; & \left[\lambda_1(x)\mathbf{1}\left\{y_{t+1}+\delta(x)'a_{t+1} > y_t+\delta(x)'a_t\right\}+\lambda_2(x)\right]^{jj_t} \\ \times\; & \left[1-\lambda_1(x)\overline{F}_u(y_t+\delta(x)'a_t|x, z_1, z_2)-\lambda_2(x)\right]^{s_t}. \end{aligned} \tag{10}$$

In these expressions, f and $\overline{F}_u$ are given by (7) and (8), respectively.

4.2 Estimation with no unobserved heterogeneity

The main difficulty in the estimation lies in the presence of MWP parameters, δ, in workers' reservation value (cf. the indicator function in equation 10). In this subsection, we present our solution to this problem in the simple case where there is no unobserved heterogeneity, for the sake of clarity. In the next subsection, we will show how to incorporate our method into an augmented EM algorithm to account for unobserved heterogeneity.

We cluster all parameters of the model into three vectors: *i*) the vector θ containing all parameters ruling the distribution of wage/amenity offers, i.e. the parameters appearing in (6); *ii*) the vector λ containing all transition parameters, related to $(\lambda_1(\cdot), \lambda_2(\cdot), \lambda_0(\cdot), q(\cdot))$; and *iii*) the vector of MWP δ. It is convenient to write the likelihood of an individual observation between t and $t+1$ as a product:

$$f_{t+1}(\theta, \lambda, \delta) = f_{1,t+1}(\theta) \times f_{2,t+1}(\theta, \lambda, \delta) \times f_{3,t+1}(\theta, \lambda, \delta),$$

where the three terms are as follows (dropping the dependence on x for conciseness):

- $f_{1,t+1}$ denotes the likelihood of the wage/amenity outcomes of non employment to job transitions:

$$f_{1,t+1}(\theta) = f(y_{t+1}, a_{t+1}; \theta)^{uj_t}.$$

- $f_{2,t+1}$ is the marginal likelihood of staying in one's job or making a job-to-job transition. It is obtained by integrating, over the wage/amenity outcomes, the contributions of job stayers ($s_t = 1$) and job changers ($jj_t = 1$) to the likelihood:

$$f_{2,t+1}(\theta, \lambda, \delta) = \left[1 - \lambda_1 \overline{F}_u(y_t + \delta' a_t; \theta) - \lambda_2\right]^{s_t} \left[\lambda_1 \overline{F}_u(y_t + \delta' a_t; \theta) + \lambda_2\right]^{jj_t}.$$

- Lastly, $f_{3,t+1}$ gathers all the remaining terms of the likelihood:

$$f_{3,t+1}(\theta, \lambda, \delta) = q^{ju_t} \lambda_0^{uj_t} \left[1 - \lambda_0\right]^{uu_t} \left[\frac{\left(\lambda_1 \mathbf{1}\left\{y_{t+1} + \delta' a_{t+1} > y_t + \delta' a_t\right\} + \lambda_2\right) f(y_{t+1}, a_{t+1}; \theta)}{\lambda_1 \overline{F}_u(y_t + \delta' a_t; \theta) + \lambda_2}\right]^{jj_t}.$$

When deciding to move to a job offering amenity a_{t+1}, workers compare their wage offer with the reservation wage $y_t + \delta'(a_t - a_{t+1})$, that depends on the MWP δ. So, because of the presence of the indicator function in the mobility rule, $f_{3,t+1}$ is not continuous in δ. We thus face a non regular estimation problem.[14] Our solution relies on the fact that, as opposed to $f_{3,t+1}$, the two terms $f_{1,t+1}$ and $f_{2,t+1}$ are continuous and twice differentiable in all their arguments. In order to estimate θ, λ, δ, we use an iterative strategy that we now detail.

Job offers. We estimate the parameters θ corresponding to wage and amenity offers only on non employment-to-job transitions (as in Christensen *et al.*, 2005). So we set:[15]

$$\widehat{\theta} = \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \ln f_{1,i,t+1}(\theta).$$

This strategy provides consistent estimates if no job offer is turned down by non employed workers. However, estimates are not efficient as we do not use the other two sources of information, given by the initial wage/amenity cross-section, and the wages and amenities of job changers.[16]

[14] Flinn and Heckman (1982) face a related problem. Specifically, the support of their likelihood depends on the reservation wage. Our case is different though, as workers can also experience constrained job-to-job transitions.

[15] In the data, t_0 and T are individual-specific but we do not write the i index for notational convenience.

[16] We tried to estimate job offer parameters jointly with all other parameters. We faced many difficulties to do so, the main one being the increase in the computational burden due to the presence of multiple binary amenities.

Transition parameters and MWP. Given the job offer parameters, the sample log-likelihood is not continuous with respect to the MWP δ. This is due to the presence of the indicator function in (10). The discontinuity greatly complicates the maximization, as usual optimization routines cannot be used. To circumvent this problem, we use the following algorithm, starting with a value for δ, say $\widehat{\delta}^{(s)}$.

1. In a first step, we maximize the likelihood with respect to λ:

$$\widehat{\lambda}^{(s+1)} = \underset{\lambda}{\text{argmax}} \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \left\{ \ln f_{2,i,t+1} \left(\widehat{\theta}, \lambda, \widehat{\delta}^{(s)} \right) + \ln f_{3,i,t+1} \left(\widehat{\theta}, \lambda, \widehat{\delta}^{(s)} \right) \right\}.$$

2. In a second step, we maximize the marginal likelihood corresponding to the job change probability, with respect to δ:

$$\widehat{\delta}^{(s+1)} = \underset{\delta}{\text{argmax}} \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \ln f_{2,i,t+1} \left(\widehat{\theta}, \widehat{\lambda}^{(s+1)}, \delta \right).$$

We iterate steps 1 and 2 until numerical convergence.

In Appendix B1, we show that this algorithm delivers consistent estimates of θ, λ, δ. Moreover, as each estimation step involves an objective function that is continuous and twice differentiable, standard routines (e.g. Newton Raphson) can be used for maximization.

Our approach uses both the event (the probability) of a job change, and the outcome (wage/amenity) of a job change in order to estimate δ. For a fixed λ, only the probability of changing job participates in the estimation of δ. However, the value of λ, that determines the constrained or voluntary nature of job mobility, is identified from the wage and amenity gains (or losses) experienced when changing job. In particular, the identification of λ_2 comes from the proportion of job changes associated with a utility loss. So, the wage/amenity outcomes of job changes, *via* the respective magnitudes of λ_1 and λ_2, are also used to determine δ.

An alternative to our strategy would be to jointly maximize the full likelihood with respect to all parameters, including δ. This would be computationally challenging, as we have to deal with five amenities and the objective function is not continuous. Moreover, the Maximum Likelihood Estimator of δ is non standard, so inference would be a difficult problem. In comparison, our parametric approach can be performed as a sequence of standard maximization steps, and well-known formulas or the bootstrap can be used to compute asympotically valid standard errors. Lastly, our approach can be easily extended in order to allow for unobserved heterogeneity, as we now show.

4.3 Accounting for unobserved heterogeneity

In the presence of unobserved heterogeneity, we have to consider the following individual random-effects likelihood:

$$\int \underbrace{f_{t_0}\left(e_0, y_0, a_0 | x, z\right)}_{f_{t_0}} \prod_{t=t_0}^{T-1} \underbrace{f_{t+1}(e_{t+1}, y_{t+1}, a_{t+1}, s_t, jj_t, ju_t, uj_t, uu_t | e_t, y_t, a_t, x, z)}_{f_{t+1}} d\Pi(z), \quad (11)$$

where $z = (z_1, z_2)$, and Π is the cdf of z, the pdf being denoted as π. It is clear from (11) that the separability properties of the type-conditional likelihood that was at the core of the method presented in the previous subsection no longer hold. Using a recently proposed version of the EM algorithm, we now show how to extend our method to allow for unobserved heterogeneity.

Using the notation of subsection 4.2., the likelihood of individual i is given by:

$$\int L_i\left(\theta, \lambda, \delta | z\right) d\Pi(z),$$

with:

$$L_i\left(\theta, \lambda, \delta | z\right) = f_{i,t_0}\left(\theta, \lambda, \delta | z\right) \prod_{t=t_0}^{T-1} f_{1,i,t+1}\left(\theta | z\right) f_{2,i,t+1}\left(\theta, \lambda, \delta | z\right) f_{3,i,t+1}\left(\theta, \lambda, \delta | z\right).$$

An important difference with the case with no unobserved heterogeneity is that we need to take into account the initial conditions term f_{i,t_0} in the likelihood (Heckman, 1981).

In order to extend the iterative algorithm presented in the previous subsection to the case with unobserved heterogeneity, we adapt the sequential EM algorithm introduced by Arcidiacono and Jones (2003). Let $\widehat{\theta}^{(s)}, \widehat{\lambda}^{(s)}, \widehat{\delta}^{(s)}$ be starting values for the parameters. There are two steps.

E-step. We compute:

$$\pi^{(s)}(z|y_i) \equiv \pi(z|y_i; \widehat{\theta}^{(s)}, \widehat{\lambda}^{(s)}, \widehat{\delta}^{(s)}) = \frac{\pi(z) L_i\left(\widehat{\theta}^{(s)}, \widehat{\lambda}^{(s)}, \widehat{\delta}^{(s)} | z\right)}{\int \pi(\widetilde{z}) L_i\left(\widehat{\theta}^{(s)}, \widehat{\lambda}^{(s)}, \widehat{\delta}^{(s)} | \widetilde{z}\right) d\widetilde{z}}.$$

M-step. We proceed sequentially:

$$\widehat{\theta}^{(s+1)} = \underset{\theta}{\operatorname{argmax}} \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \int \pi^{(s)}(z|y_i) \ln f_{1,i,t+1}(\theta|z)\, dz.$$

$$\widehat{\lambda}^{(s+1)} = \underset{\lambda}{\operatorname{argmax}} \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \int \pi^{(s)}(z|y_i) \ln \left\{ f_{2,i,t+1}\left(\widehat{\theta}^{(s+1)}, \lambda, \widehat{\delta}^{(s)}|z\right) f_{3,i,t+1}\left(\widehat{\theta}^{(s+1)}, \lambda, \widehat{\delta}^{(s)}|z\right) \right\} dz.$$

$$\widehat{\delta}^{(s+1)} = \underset{\delta}{\operatorname{argmax}} \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \int \pi^{(s)}(z|y_i) \ln f_{2,i,t+1}\left(\widehat{\theta}^{(s+1)}, \widehat{\lambda}^{(s+1)}, \delta|z\right) dz.$$

We iterate the E and M steps until numerical convergence.

Recall that $f_{3,i,t+1}$ is not continous with respect to MWP δ. The sequential approach we adopt avoids having to maximize this term with respect to δ. As in the case with no unobserved heterogeneity, the δ parameters are directly estimated on the probability to change job but also depend indirectly on the outcomes of job changes, *via* the values of λ and θ. Also, in each M-step we estimate the job offer parameters only on non employment-to-job transitions.

We show in Appendix that the estimator satisfies asymptotically some population moment conditions. As in the case with no unobserved heterogeneity, the estimator is consistent. A difference with the case with no unobserved heterogeneity is that we do not iterate on λ and δ for each estimate of the offer parameters θ (as in Meng and Rubin, 1993).

Lastly, in practice we specify: $z_1 = w_1 + \beta w_2$, and $z_2 = w_2$, with w_1 and w_2 independent and normally distributed. We discretize the space of (w_1, w_2) in order to compute the integrals as sums, using 5-by-5 points of support. Therefore, each M-step involves a limited number of computations. As for inference, although asymptotic standard errors can in theory be obtained by the usual method-of-moments formula, we found it more convenient to use nonparametric bootstrap clustered at the individual level (100 replications).

5 Estimation results

In this section we present the results of the estimation of the benchmark model derived in sections 2 and 4. We focus on two features: workers' MWP for amenities and labor turnover.

5.1 Marginal Willingness to Pay for amenities

Table 2 presents the results on workers' propensity to pay for amenities. As mentioned in section 4, each MWP δ (we drop the k subscript for convenience) is modelled as: $\delta = \delta_{\text{age}>35} \cdot \mathbf{1}\{\text{age} > 35\} + \delta_{\text{col. edu.}} \cdot \mathbf{1}\{\text{col. edu.}\} + \delta_{\text{cst}}$. For each job characteristic, the first three rows in the Table show the estimates of $(\delta_{\text{age}>35}, \delta_{\text{col. edu.}}, \delta_{\text{cst}})$ while the fourth row presents the mean value (in the sample) of δ.

Table 2 about here

First, the mean MWP are always positive except in a few cases for which the estimate is not significant. Also, the mean values are very rarely under 10%, which indicates that improving some non wage dimension of a job is equivalent to a substantial wage increase. In most cases, this increase is significant and ranges between 20% and 40%. These estimates show rather strong individual preferences for amenities, in line with the findings of the studies following Gronberg and Reed (1994). In section 6, we analyze why these results differ from those obtained within a hedonic regression approach.

Before turning to the effect of individual characteristics on preferences for amenities, we study the dispersion of mean MWP values along two dimensions: countries and amenities. Looking at Table 2 from left to right shows that preferences for a given amenity can differ greatly between countries. For example, Finnish and French workers put no weight at all on the type of work, whereas in all other countries workers are willing to pay at least 20% of their wage to improve this amenity. French workers are by far those who care the most about working times while in three countries (Austria, Finland and Portugal) this amenity does not enter the utility function at all. The only two job characteristics for which the MWP remain high and significant in all countries are distance to work and job security.

Looking at Table 2 from top to bottom reveals that, in each country, the MWP for job security is always among the highest if not, in five countries out of eight, the highest.[17] French workers tend to put a little more weight on distance to job and working times while Austrian and Dutch workers prefer the amenity type of work slightly more. Still, the general

[17] This result could be partly driven by the fact that transition probabilities do not depend on job security in the model. However, letting the search environment depend on amenities raises methodological issues that go beyond the scope of this paper, see footnote (7).

picture arising from Table 2 is that European workers are willing to pay a substantial amount to go to more secure jobs.

The descriptive statistics in Table 1 showed that some Latin countries (France, Italy and Portugal) have rather static labor markets while Northern European countries (Denmark, Finland and the Netherlands) show much more labor turnover (see also transition parameter estimates in Table 3 below). However, the estimates reported in Table 2 show that neither Latin nor Northern European countries form an homogeneous group with respect to MWP for amenities. Therefore the differences between European countries based on workers' preferences for job characteristics do not match the picture of labor market dynamics.

Turning to the effects of individual covariates on δ, one can see that age and education seldom have a significant effect on MWP, and that there is no general pattern across countries or amenities. The two countries where MWP depend the most on individual characteristics are France and the Netherlands. French workers above 35 have stronger preferences for working conditions, working times and job security than younger workers. On the contrary, in Finland and in the Netherlands, younger workers put more weight on working times.

As for education, French workers who went to college have weaker preferences than less educated ones for all job characteristics except working conditions. Likewise, less educated Italian and Portuguese workers put more weight on job security. These results suggest that, in these countries, workers' selection between jobs depends more on amenities for low-skilled than for high-skilled workers. This could be the case if the less educated faced more wage rigidity.

5.2 Labor turnover

We show in Table 3 the arrival rates of job offers and employment shocks. Each arrival rate $\lambda \in \{\lambda_1, \lambda_2, \lambda_0, q\}$ is modelled as: $\ln \lambda = \lambda^{\ln}_{\text{age}>35} \cdot \mathbf{1}\{\text{age} > 35\} + \lambda^{\ln}_{\text{col. edu.}} \cdot \mathbf{1}\{\text{col. edu.}\} + \lambda^{\ln}_{\text{cst}}$. For each arrival rate, the first three rows show the estimates of $(\lambda^{\ln}_{\text{age}>35}, \lambda^{\ln}_{\text{col. edu.}}, \lambda^{\ln}_{\text{cst}})$ while the fourth row presents the sample average of λ.

All mean transition parameter estimates are significant. Reallocation shocks ruled by λ_2 are roughly of the same order of magnitude as job destruction shocks q. In particular, a model with no reallocation shock is rejected by the data. Still, λ_2 is much lower than the probability of receiving an outside job offer λ_1 (up to ten times lower in Italy).

The results in Table 3 are consistent with the descriptive statistics shown in Table 1. For example, we note that the probability to be reallocated across jobs is lowest in Austria, France, Italy and Portugal, while it is highest in Denmark. Spain differs from the other Latin countries, probably because of the extensive use of short term employment contracts, which is consistent with the very high job-to-non employment probability in this country.

Contrary to what we noted for MWP, individual characteristics often have a significant effect on transition parameters. Being above 35 decreases the probabilities to experience a job reallocation and to move between employment and non employment, meaning that younger workers are more mobile. In contrast, the effect of age on the probability to receive an offer through on-the-job search is not homogeneous across countries. Being above 35 reduces on-the-job search in France and in the Netherlands while it has an opposite effect almost everywhere else, especially in Spain. Note that, as we mention in footnote (11), results on the effect of age call for prudence as we assume that workers do not anticipate the changes in their search environment (or in their preferences) as they grow older.

Table 3 about here

College education decreases the probability to be reallocated across jobs and to go to non employment, while it increases the arrival rate of job offers when not employed (except in Austria). The effect of going to college on on-the-job search differs between countries and is rarely significant. However, it is rather high in Austria (though not significant), Finland and Portugal.

Looking at the ratio $\kappa = \lambda_1/(\lambda_2 + q)$ yields a rather heterogeneous picture of search frictions across Europe. France is the country with the most search frictions (κ is the lowest) whereas Spanish and Finnish workers face the highest values of κ.

The next to last row of Table 3 shows the probability to make a voluntary job-to-job transition, conditional on being employed. This probability can be computed from the estimates of transition parameters as:[18,19]

$$\begin{aligned}\mathbb{P}(\text{volmov}) &= \mathbb{E}\left(\lambda_1 \overline{F}_u(u)\right) \\ &= \frac{\lambda_1}{\kappa}\left[\frac{1+\kappa}{\kappa}\ln(1+\kappa) - 1\right]. \end{aligned} \tag{12}$$

The probability to move voluntarily between jobs is the highest in Spain and the lowest in Portugal. Overall, we can see that this probability is quite low in Europe, between 3.6% and 9.5% per year. As (12) shows, $\mathbb{P}(\text{volmov})$ is not only a function of κ, so the dispersion of this probability across countries does not exactly match that of search frictions. It is also possible to compare $\mathbb{P}(\text{volmov})$ with the probability $\mathbb{P}(\text{cstmov})$ of making a constrained job-to-job transition, which is simply equal to λ_2. The last line of Table 3 shows the ratio of these two probabilities. It reveals no regular pattern. In some countries with dynamic labor markets, for example in Denmark, job-to-job mobility can be due to a substantial share of constrained job reallocations, while static labor markets such as Portugal may also present a large proportion of job reallocations. Likewise, voluntary mobility can be high with respect to constrained mobility in countries with a high (Spain) or a low (Italy) job-to-job turnover (see Table 1 for the overall probabilities of changing job).

Now, our distinction between voluntary and constrained mobility strongly depends on our modelling of job change decisions. As shown in section 2, we assume that amenities can enter workers' utility so that the variable of interest when deciding to change job is a weighted sum of log-wages and amenities: $y + \delta' a$. In the rest of this section, we show how the omission of non monetary job characteristics in workers' preferences for jobs is likely to bias the analysis of labor turnover and search frictions. To this end, we estimate the model setting the MWP parameters δ to zero. The resulting parameter estimates are then used to compute the probabilities to make a voluntary or a constrained transition, as well as the index of search frictions κ. In Figure 1, we plot these three estimates against their counterparts from the unrestricted model (in which δ is estimated). The dashed line is the 45 degree line.

[18] We drop the conditioning on observed and unobserved heterogeneity for notational convenience.

[19] The second equality follows from:

$$\mathbb{E}\left(\overline{F}_u(u)\right) = \int \overline{F}_u(u) g_u(u) du = \int \overline{F}_u(u) \frac{(1+\kappa) f_u(u)}{\left[1+\kappa \overline{F}_u(u)\right]^2} du = (1+\kappa)\int_0^1 \frac{u}{\left[1+\kappa u\right]^2} du.$$

Figure 1 about here

Overlooking amenities when studying labor turnover can lead to two types of errors. First, job changes associated with an increase in utility but also with a wage cut (and large gains in amenities) may wrongly be interpreted as constrained. Second, some job changes going with a wage increase may also be wrongly classified as voluntary if they are actually associated with a large loss in amenities and are thus involuntary. The first type of error would mechanically increase the share of constrained transitions whereas the second type would decrease it. The first two graphs of Figure 1 show that $\mathbb{P}(\text{volmov})$ is lower and $\mathbb{P}(\text{cstmov})$ is higher when setting MWP to zero. Therefore, the first type of error dominates in all the countries we study, meaning that, overlooking the role of amenities in mobility decisions, one tends to overestimate the share of constrained job-to-job transitions. Accordingly, the index of search frictions κ is lower (mobility to better jobs is slower) when setting MWP to zero (see the third graph of Figure 1). In quantitative terms, setting δ to zero implies an underestimation of κ of 15% (Austria) to 50% (Portugal).

6 Compensating differentials in cross-section

In this section we use the model to compute and interpret compensating wage differentials in a cross-section of employed workers, comparing them to MWP and wage/amenity correlations in job offers. Then, we study the sensitivity of these wage differentials to the degree of search frictions. Lastly, we perform a similar exercise on compensating wage differentials in the population of job changers.

6.1 The stationary distribution of wages and amenities.

We start by running the following hedonic regression in the steady-state cross-section of employed workers:

$$y = \Delta' a + \beta_x' x + \beta_1 z_1 + \beta_2 z_2 + \varepsilon. \quad (13)$$

The linear projection coefficients Δ are the "compensating" wage differentials associated with the various amenities. So, as the stationary pdf of wages and amenities given by equation (5), Δ is a function of three sets of parameters: the wage/amenity correlation in offers ρ, the preference parameters δ, and the search frictions index κ.[20] In this subsection we focus on the relation between compensating differentials Δ and MWP δ. The next subsection will focus on the role of search frictions κ.

In order to estimate Δ we use a simulation technique to produce a cross-section of wage and amenities among employed workers. Specifically, we draw from the wage/amenity offer distribution and use the accept-reject principle to draw from g (see e.g. Robert and Casella, 2004, p. 47).[21] We use 30 draws by individual, for each values of the discretized unobserved heterogeneity distribution. The results of the hedonic regression are shown in Table 4.

Table 4 about here

Comparing Table 4 with Table 2 shows a striking contrast between the MWP estimates and the estimates of wage differentials in cross-section. Indeed, Table 2 showed strong individual preferences for amenities. Table 4 shows that these preferences are not reflected in cross-section as most Δ estimates are insignificant and in many cases positive, i.e. of the "wrong" sign (the only exceptions being distance to work in Italy and working conditions in the Netherlands). Hence, the model is consistent with both strong preferences for amenities– in line with the job duration estimates following Gronberg and Reed (1994)– and small wage differentials. It thus provides a framework to understand the mostly inconclusive results obtained using hedonic wage regressions.

In Figure 2 we show the link between Δ and (δ, ρ). For each country, the graph on the left shows the wage differential Δ against the MWP δ for each amenity. We add the counter-diagonal to the graph as the more are compensating differentials driven by workers' preferences, the closer Δ should be to $-\delta$. We see no negative pattern at all. This makes it clear that wage differentials are far from reflecting workers' preferences for amenities.

Figure 2 about here

On the same figure, the graphs on the right plot Δ against ρ.[22] We note that the observations are very much concentrated around the 45 degree line. So, the wage differentials

[20] Δ may also depend on the distribution of observed and unobserved heterogeneity (x, z_1, z_2). In (5), δ and κ are actually functions of x, and the wage/amenity pdf is conditional on (x, z_1, z_2).

[21] Drawing from f is justified as equation (5) implies that: $\frac{g}{f} \leq (1 + \kappa)$.

[22] The estimates of the ρ parameters are shown in Table C1 in Appendix C. As for δ, our comments are based on mean parameter estimates.

in cross-section are close to the ones that would have been obtained, had workers not selected themselves between jobs. Indeed, if there were no voluntary job changes we would have $\Delta = \rho$. This means that in our data, compensating differentials are mostly driven by the wage/amenity correlation in job offers, i.e. by the posting behaviour of firms, rather than by workers' preferences. Going back to the steady-state relation (5), we can see that such a situation would take place for very low values of κ (if $\kappa \to 0$, $g \to f$). This suggests that search frictions could account for the absence of compensating differentials in cross-section. We take a closer look at this issue in the next subsection.

6.2 Search frictions and compensating differentials

In the model, jobs are ranked according to their utility level. On-the-job search allows workers to climb up the job ladder, reaching higher utility levels, while adverse shocks such as job destruction or reallocation shocks may force them to lower rungs of the ladder. Moreover, an increase in utility can be due to a higher wage or better amenities. When changing job voluntarily, workers may thus trade off wages for better non wage characteristics. The larger the share of voluntary job changes, the more this mechanism is at play. So, we should intuitively observe that a larger κ yields a more negative correlation between wages and amenities in cross-section.

To test this intuition, we increase the search frictions index κ and compute the associated compensating wage differentials in cross-section. We run the hedonic regression (13) on a simulated cross-section of employed workers, setting all parameters at the values estimated in section 4, except the search frictions index κ which we set to 30. We thus simulate a steady-state distribution in an economy where workers receive on average 30 outside offers between two adverse shocks.

The results of this exercise are shown in Table 5. The wage differentials associated with the various amenities tend indeed to be more negative for this high value of κ, compared to the benchmark estimates of Table 4. However, they still bear little resemblance with the underlying preference parameters δ. While the positive wage premia observed in many cases in Table 4 have now mostly disappeared, we do not observe a clear pattern of wage differentials for amenities. This suggests than even unrealistically low levels of search frictions (i.e. a very large κ) are unable to yield substantial compensating differentials.

Table 5 about here

Now, as shown in subsection 6.1, our estimates of compensating differentials are mostly driven by the wage/amenity correlations in job offers ρ. In the model, these parameters are assumed exogenous as we do not model labor demand. However, one could expect these correlations to be affected by the index of search frictions as a higher κ increases competition for workers between firms. Therefore, it could be that the high value of κ we used in Table 5 also influences ρ. For this reason, and in order to have a more precise look at the role of search frictions in compensating differentials, we run a series of simulations setting the ρ parameters to zero. This will allow us to see the partial effect of search frictions on compensating differentials in an economy where the only two sources of correlation between wages and amenities are workers' preferences and search frictions.

Specifically, we set the ρ parameters to zero and run the hedonic regression (13) on a series of samples simulated using different values of κ.[23] We go from markets with a high level of search frictions ($\kappa = 1$) to markets where workers can rapidly climb the wage ladder ($\kappa = 30$). The resulting compensating differentials are shown in Figure 3.

Figure 3 about here

We can see on Figure 3 that compensating wage differentials in cross-section start from zero as there is no wage/amenity correlation in offers. Then, except in the few cases for which the estimates of MWP are not significantly negative, wage differentials tend to decrease when the index of search frictions increases. Moreover, the negative slope is steeper for high values of δ (see Table 2). For example, in most countries we note that the wage differential for job security shows the most negative values when κ gets large, consistently with the high values we estimated for the associated MWP. This feature is particularly striking in France: the two amenities for which we found no significant MWP (type of work and working conditions) correspond to a relatively flat profile, while the other three amenities, for which preferences were found to be strong, are associated with rapidly decreasing wage differentials when κ increases.

Still, even for very large values of κ, the wage differentials are, in absolute value, much lower than the associated MWP. For example in the Netherlands, the ratio $|\Delta|/\delta$ is around

[23] These values are 1, 2, 5, 7, 10, 12, 15, 17, 20, 25 and 30.

10% for the amenity type of work. Hence, in this partial equilibrium model where wage and amenity offers are not correlated and workers' preferences for amenities are strong, a very small degree of search frictions is sufficient for hedonic wage regressions to be unable to reveal workers' MWP for amenities.

6.3 Using job change outcomes to study compensating differentials

The previous subsection showed that an on-the-job search model can produce wage/amenity correlations slightly in accordance with workers' preferences only when the index of search frictions is unrealistically high. In this subsection, we address the following question: Can we find evidence of compensating wage differentials using another cross-section of wages and amenities?

Since the key feature of the model that could yield compensating differentials is workers' decision to move between jobs, it makes sense to look at the distribution of wage/amenity outcomes of job changes. Importantly, these are not the outcomes of mobility decisions, for two reasons: we do not consider workers who prefer to stay in their current job, and some of the job changes might be constrained job reallocations. Using the steady-state relation (3), we can write the stationary distribution of wages and amenities posterior to a job change, denoted as j, as:

$$j(y,a) = \frac{f(y,a)h(y,a)}{\int f(\widetilde{y},\widetilde{a})h(\widetilde{y},\widetilde{a})d\widetilde{y}d\widetilde{a}}, \quad \text{where} \quad h(y,a) = \frac{F_u(y+\delta' a)}{1+\kappa \overline{F}_u(y+\delta' a)} + \frac{\lambda_2}{\lambda_1}. \tag{14}$$

We note that the mapping (14) between MWP and j involves f and κ, as was the case for g in (5), but also the ratio of arrival rates of reallocation shocks and outside job offers, λ_2/λ_1.

We thus estimate the hedonic regression (13) on a simulated cross-section of job changers. We denote as Δ^m the corresponding vector of wage differentials and show the estimation results in Table 6. As in the stationary distribution of employed workers (see Table 4), we find almost no significant compensating wage differentials.

Table 6 about here

Then, we run another series of simulations setting ρ to zero. Moreover, we set κ to its estimated value (Table 3) and we vary the ratio λ_2/λ_1.[24] Therefore, we vary the distribution posterior to job change while keeping the steady-state distribution g fixed. The results are shown in Figure 4.

Figure 4 about here

We find that compensating wage differentials are increasing with the ratio λ_2/λ_1. Interestingly, when $\lambda_2 = 0$, the model can generate compensating differentials in the cross-section of job changers even if κ is set to its estimated value. Therefore, in a partial equilibrium on-the-job search model with no wage/amenity correlation in job offers and no reallocation shocks, there could be compensating wage differentials in the cross-section of job changers and no wage/amenity compensation in the cross-section of employed workers (as shown in Figure 3, when κ equals its estimated value). Still, even in that case, the ratio $|\Delta^m|/\delta$ is well below one. Then, as we introduce reallocation shocks and thus increase λ_2/λ_1, we can see that the compensating differentials become less and less negative and converge to zero for large values of λ_2/λ_1. For instance, the case $\lambda_2 = 0$ suggests that one can read the strong preference for job security in the distribution of job changers, as this amenity is associated with a wage penalty of almost 10% in most countries. However, a 10% share of constrained transitions yields wage differentials that are much closer to zero.

This exercise shows that, contrary to the stationary distribution of employed workers, the distribution of wages and amenities posterior to job change could be a guide to reveal workers' preferences if job-to-job transitions were only voluntary. However, it becomes less relevant as the share of constrained job reallocations increases.

7 Conclusion

We have estimated a partial equilibrium on-the-job search model with two types of job-to-job mobility (voluntary and constrained), two types of individual unobserved heterogeneity, and six job characteristics (the wage plus five amenities). Our estimates reveal strong preferences for some job characteristics, job security coming out as the amenity for which workers are

[24] We have set λ_2/λ_1 to the following values: 0, .025, .05, .075, .1, .125, .15, .175, .2, .225 and .25. Note that, as we fix $\kappa = \lambda_1/(\lambda_2 + q)$ to a positive value (the one estimated in Table 3), λ_2/λ_1 has to be lower than $1/\kappa$.

the most willing to pay across Europe. However, these preferences do not translate into compensating wage differentials in cross-section because of the wage/amenity correlation in job offers and because of search frictions. Even when looking at the sample of job changers, we can hardly detect compensating differentials as workers experience constrained job reallocations which hinder their upward mobility on the job ladder. Moreover, for individual preferences for amenities to be (albeit imperfectly) reflected in cross-section, one would need extremely low levels of search frictions, or no constrained job-to-job transitions at all.

The main limitation to our approach is that labor demand is treated as exogenous. In particular, the correlations between wages and amenities in job offers, which turn out to play a very important role in compensating wage differentials in cross-section, are primitives of our model. However, as we mention in 6.2, these correlations can be affected by the degree of search frictions since these enter firms' job posting program. Addressing this issue requires to introduce the production cost functions of amenities as well as the distribution of productivities among firms. Hwang *et al.* (1998) run such an analysis but do not fully take their model to the data. We see the present paper as a first step towards estimation of job search models with multiple amenities.[25]

The main obstacle standing in the way of this extension is a data issue. Indeed, recent developments in the empirical job search literature aim at estimating equilibrium models with both worker and firm heterogeneity using matched employer-employee data (see Postel-Vinay and Robin, 2002). Introducing amenities in these models would also require these matched data sets to provide information on some non monetary characteristics of jobs. We are not aware of the availability of such a data set yet.

References

Arcidiacono P, Jones J 2003. Finite Mixture Distributions, Sequential Likelihood and the EM Algorithm, *Econometrica*, **71**, 933-46.

Brown C. 1980. Equalizing Differences in the Labor Market, *Quarterly Journal of Economics*, **94**, 113-34.

[25] Dey and Flinn (2005) estimate an equilibrium job search model where workers care for income and one amenity (health insurance coverage).

Burdett K, Coles M. 2003. Equilibrium Wage-Tenure Contracts, *Econometrica*, **71**, 1377-404.

Burdett K, Mortensen D. 1998. Wage Differentials, Employer Size and Unemployment, *International Economic Review* **39**, 257-73.

Christensen B, Lentz R, Mortensen D, Neumann G, Werwatz A. 2005. On the Job Search and the Wage Distribution, *Journal of Labor Economics*, **23**, 31-58.

Cox D. 1975. Partial Likelihood, *Biometrika*, **62**, 269-276.

Dale-Olsen H. 2006. Estimating Workers' Marginal Willingness to Pay for Safety Using Linked Employer-Employee Data, *Economica*, **73**, 99-127.

Daniel C, Sofer C. 1998. Bargaining, Compensating Wage Differentials and Dualism of the Labor Market. Theory and Evidence for France, *Journal of Labor Economics*, **16**, 546-75.

Dempster A, Laird N., Rubin D. 1977. Maximum Likelihood from Incomplete Data via the EM Algorithm, *Journal of the Royal Statistical Society*, **B 39**, 1-38.

Dey M, Flinn C. 2005. An Equilibrium Model of Health Insurance Provision and Wage Determination, *Econometrica*, **73**, 571-627.

Dey M, Flinn C. 2008. Household Search and Health Insurance Coverage, forthcoming in *Journal of Econometrics*.

Duncan G, and Holmlund B. 1983. Was Adam Smith Right After All? Another Test of the Theory of Compensating Differentials, *Journal of Labor Economics*, **1**, 366-79.

Flinn C, Heckman J. 1982. New Methods for Analyzing Structural Models of Labor Force Dynamics, *Journal of Econometrics*, **18**, 115-68.

Goddeeris J. 1988. Compensating Differentials and Self-Selection: An Application to Lawyers, *Journal of Political Economy*, **96**, 411-28.

Gronberg T, Reed W. 1994. Estimating Workers' Marginal Willingness to Pay for Job Attributes Using Duration Data, *Journal of Human Resources*, **29**, 911-31.

Heckman J. 1981. The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time - Discrete Data Stochastic Process. In *Structural Analysis of Discrete Data with Econometric Applications*, Manski C, McFadden D (eds). Cambridge: MIT Press.

Herzog H, Schlottmann A. 1990. Valuing Risk in the Workplace: Market Price, Willingness to Pay, and the Optimal Provision of Safety, *Review of Economics and Statistics*, **72**, 463-70.

Hwang H, Mortensen D, Reed W. 1998. Hedonic Wages and Labor Market Search, *Journal of Labor Economics*, **16**, 815-47.

Hwang H, Reed W, Hubbard C. 1992. Compensating Differentials and Unobserved Productivity, *Journal of Political Economy*, **100**, 835-58.

Jolivet G, Postel-Vinay F, Robin J-M. 2006. The Empirical Content of the Job Search Model: Labor Mobility and Wage Distributions in Europe and the US, *European Economic Review*, **50**, 877-907.

Kostiuk P. 1990. Compensating Differentials for Shift Work, *Journal of Political Economy*, **98**, 1054-75.

Lang K, Majumdar S. 2004. The Pricing of Job Characteristics When Markets do not Clear: Theory and Policy Implications, *International Economic Review*, **45**, 1111-28.

Meng X-L, Rubin D. 1993. Maximum Likelihood Estimation via the ECM Algorithm: A General Framework, *Biometrika*, **80**, 267-278 .

Postel-Vinay F, Robin J-M. 2002. Equilibrium Wage Dispersion with Worker and Employer Heterogeneity, *Econometrica*, **70**, 2295-350.

Ridder G, van den Berg G. 2003. Measuring Labor Market Frictions: A Cross-Country Comparison, *Journal of the European Economic Association*, **1**, 224-44.

Robert C, Casella G. 2004. *Monte Carlo Statistical Methods*, Springer-Verlag, New York.

Rosen S. 1974. Hedonic Prices and Implicit Markets: Product Differentiation in Pure Competition, *Journal of Political Economy*, **82**, 34-55.

Rosen S. 1986. The Theory of Equalizing Differences. In *Handbook of Labor Economics*, vol 1:2 641-92, Ashenfelter O, Card D (eds). Amsterdan: Elsevier Science.

Senick C. 2005. What Can We Learn from Subjective Data: the Case of Income and Well-Being, *Journal of Economic Surveys*, **19**, 43-63.

Shimer R. 2005. The Cyclicality of Hires, Separations and Job-to-Job Transitions, *Federal Reserve Bank of St. Louis Review*, **87**, 493-507.

Smith A. 1976. *An Inquiry into the Nature and Causes of the Wealth of Nations*, Cannan E (ed). University of Chicago press.

Thaler R, Rosen S. 1975. The Value of Saving a Life: Evidence from the Labor Market. In *Household Production and Consumption*, Terleckyj N (ed). New York: NBER.

Van Ommeren J, van den Berg G, Gorter C. 2000. Estimating the Marginal Willigness to Pay for Commuting, *Journal of Regional Science*, **40**, 541-63.

TABLES AND FIGURES

Table 1: Descriptive statistics

	AUS	DNK	ESP	FIN	FRA	ITA	NLD	PRT
Individuals	1 862	1 721	3 732	1 692	3 626	3 880	2 907	2 684
Job spells	2 226	2 580	5 151	2 067	4 537	4 710	3 883	3 344
Non employment spells	453	516	1 644	514	1 247	1 413	587	769
Average #spells/individual	1.44	1.80	1.82	1.53	1.60	1.58	1.54	1.53
% of job spells ending with...								
a job-to-job transition	.14	.30	.21	.16	.15	.13	.22	.16
a job-to-non employment transition	.15	.12	.19	.12	.17	.20	.09	.15
Non employment-to-job transitions	175	287	1 008	295	724	710	336	397
Average durations:								
job spells	3.37	2.94	2.88	2.72	3.66	3.55	3.39	3.62
non employment spells	2.25	1.87	1.82	1.61	1.90	2.40	1.90	2.05
% of job changes...								
with a wage increase	.57	.54	.56	.64	.59	.57	.68	.60

Table 2: MWP estimates

	AUS	DNK	ESP	FIN	FRA	ITA	NLD	PRT
				Type of work				
$\delta_{\text{age}>35}$	−.131 (.18)	−.034 (.16)	.030 (.07)	−.081 (.43)	−.074 (.15)	.194 (.15)	−.044 (.15)	−.103 (.23)
$\delta_{\text{col. edu.}}$	−.132 (.11)	−.010 (.27)	−.091 (.07)	.148 (.13)	−.195 (.13)	−.111 (.18)	−.357 (.19)	−.317 (.29)
δ_{cst}	.404 (.14)	.237 (.10)	.195 (.07)	.018 (.44)	.081 (.09)	.177 (.07)	.460 (.11)	.430 (.20)
δ (mean)	.324 (.09)	.217 (.10)	.190 (.04)	.016 (.18)	−.002 (.08)	.271 (.08)	.367 (.09)	.361 (.13)
				Working conditions				
$\delta_{\text{age}>35}$	−.035 (.18)	−.013 (.18)	.028 (.06)	−.018 (.19)	.304 (.14)	.036 (.15)	−.184 (.13)	−.031 (.20)
$\delta_{\text{col. edu.}}$	−.091 (.10)	.056 (.27)	.087 (.08)	−.008 (.16)	.296 (.13)	.110 (.21)	−.118 (.18)	−.036 (.33)
δ_{cst}	.153 (.17)	.130 (.14)	.033 (.05)	.084 (.18)	−.310 (.10)	−.130 (.08)	.278 (.08)	−.107 (.19)
δ (mean)	.128 (.10)	.141 (.11)	.066 (.03)	.070 (.08)	−.090 (.07)	−.104 (.08)	.152 (.07)	−.125 (.12)
				Working times				
$\delta_{\text{age}>35}$	.142 (.20)	−.014 (.18)	−.127 (.07)	−.381 (.15)	.321 (.13)	.163 (.12)	−.225 (.12)	.011 (.22)
$\delta_{\text{col. edu.}}$	.187 (.14)	.124 (.30)	.011 (.07)	−.049 (.09)	−.338 (.10)	−.124 (.17)	.404 (.21)	.571 (.39)
δ_{cst}	−.071 (.19)	.189 (.12)	.138 (.06)	.231 (.14)	.360 (.08)	.127 (.08)	.228 (.09)	−.093 (.20)
δ (mean)	.019 (.12)	.220 (.11)	.078 (.03)	−.016 (.07)	.434 (.07)	.204 (.07)	.180 (.07)	−.054 (.12)
				Distance to work				
$\delta_{\text{age}>35}$	−.121 (.11)	−.027 (.16)	−.148 (.07)	−.041 (.14)	−.078 (.10)	.019 (.08)	−.080 (.11)	−.145 (.18)
$\delta_{\text{col. edu.}}$	.019 (.04)	.002 (.22)	.023 (.06)	−.078 (.10)	−.326 (.10)	−.077 (.16)	.076 (.16)	.620 (.39)
δ_{cst}	.201 (.11)	.274 (.09)	.304 (.05)	.212 (.12)	.521 (.07)	.188 (.05)	.245 (.08)	.231 (.14)
δ (mean)	.136 (.07)	.260 (.09)	.237 (.04)	.162 (.06)	.405 (.06)	.193 (.05)	.215 (.06)	.197 (.08)
				Job security				
$\delta_{\text{age}>35}$	−.269 (.16)	.148 (.16)	−.159 (.08)	−.373 (.49)	.251 (.12)	.124 (.18)	−.141 (.11)	−.496 (.44)
$\delta_{\text{col. edu.}}$	−.105 (.11)	.343 (.37)	−.226 (.07)	.034 (.21)	−.442 (.13)	−.407 (.23)	−.033 (.15)	−.797 (.56)
δ_{cst}	.454 (.14)	.296 (.10)	.674 (.06)	.752 (.50)	.366 (.09)	.490 (.09)	.397 (.09)	1.21 (.42)
δ (mean)	.300 (.09)	.482 (.13)	.549 (.05)	.537 (.22)	.382 (.07)	.527 (.11)	.312 (.06)	.921 (.25)

Table 3: Transition parameter estimates

	AUS	DNK	ESP	FIN	FRA	ITA	NLD	PRT
				λ_1				
$\ln \lambda^{\ln}_{1,\text{age}>35}$	.135 (.45)	−.266 (.30)	.555 (.19)	.498 (.33)	−.525 (.24)	.224 (.27)	−.929 (.26)	.338 (.33)
$\ln \lambda^{\ln}_{1,\text{col. edu.}}$	.927 (.67)	−.245 (.29)	.038 (.21)	.780 (.29)	.356 (.22)	−.109 (.42)	−.523 (.33)	1.14 (.47)
$\ln \lambda^{\ln}_{1,\text{cst}}$	−2.08 (.50)	−1.09 (.18)	−1.30 (.14)	−1.95 (.31)	−1.96 (.15)	−1.76 (.11)	−1.11 (.16)	−2.37 (.19)
λ_1 (mean)	.149 (.06)	.275 (.04)	.374 (.03)	.272 (.06)	.125 (.02)	.193 (.03)	.203 (.03)	.126 (.03)
				λ_2				
$\ln \lambda^{\ln}_{2,\text{age}>35}$	−1.75 (.31)	−1.08 (.14)	−1.36 (.15)	−1.27 (.23)	−1.48 (.17)	−1.04 (.16)	−1.24 (.17)	−1.37 (.17)
$\ln \lambda^{\ln}_{2,\text{col. edu.}}$	−.562 (.44)	−.113 (.15)	−.817 (.15)	−.165 (.19)	−.046 (.18)	−1.15 (.48)	.314 (.22)	−.776 (.41)
$\ln \lambda^{\ln}_{2,\text{cst}}$	−2.97 (.19)	−2.15 (.09)	−2.49 (.10)	−2.71 (.16)	−3.16 (.10)	−3.51 (.12)	−2.77 (.11)	−2.99 (.09)
λ_2 (mean)	.027 (.004)	.074 (.005)	.046 (.003)	.036 (.004)	.026 (.002)	.019 (.002)	.040 (.003)	.031 (.002)
				λ_0				
$\ln \lambda^{\ln}_{0,\text{age}>35}$	−.803 (.09)	−.637 (.09)	−.438 (.06)	−.535 (.09)	−.748 (.05)	−.599 (.04)	−.625 (.08)	−.535 (.07)
$\ln \lambda^{\ln}_{0,\text{col. edu.}}$	−.194 (.25)	−.047 (.09)	.013 (.17)	.107 (.11)	.186 (.06)	.165 (.18)	.246 (.12)	.126 (.16)
$\ln \lambda^{\ln}_{0,\text{cst}}$	−.612 (.07)	−.578 (.06)	−.670 (.05)	−.480 (.06)	−.588 (.04)	−.915 (.04)	−.559 (.07)	−.761 (.06)
λ_0 (mean)	.374 (.02)	.418 (.02)	.425 (.02)	.480 (.02)	.434 (.01)	.310 (.01)	.445 (.02)	.376 (.02)
				q				
$\ln q^{\ln}_{\text{age}>35}$	−.135 (.13)	−.528 (.11)	−.580 (.07)	−.501 (.11)	−.699 (.08)	−.574 (.07)	−.436 (.10)	−.236 (.09)
$\ln q^{\ln}_{\text{col. edu.}}$	−1.16 (.38)	−.677 (.12)	−.788 (.09)	−.899 (.16)	−.146 (.09)	−.623 (.17)	−.307 (.15)	−.346 (.25)
$\ln q^{\ln}_{\text{cst}}$	−3.19 (.11)	−2.53 (.08)	−2.18 (.05)	−2.23 (.07)	−2.57 (.06)	−2.68 (.05)	−3.10 (.08)	−3.03 (.07)
q (mean)	.037 (.003)	.053 (.003)	.078 (.003)	.066 (.004)	.056 (.003)	.051 (.002)	.035 (.002)	.042 (.002)
				Search frictions index				
κ (mean)	3.31 (1.90)	2.46 (.56)	4.29 (.53)	4.12 (1.5)	1.67 (.36)	3.30 (.86)	2.66 (.70)	2.13 (.69)
				Job-to-job mobility				
$\mathbb{P}$(volmov)	.042 (.01)	.086 (.007)	.095 (.005)	.069 (.007)	.043 (.003)	.054 (.004)	.059 (.005)	.036 (.004)
$\mathbb{P}$(volmov)/$\mathbb{P}$(cstmov)	1.56 (.65)	1.15 (.16)	2.07 (.23)	1.91 (.37)	1.65 (.24)	2.85 (.42)	1.47 (.23)	1.27 (.22)

Table 4: Compensating differentials in the steady-state distribution

	AUS	DNK	ESP	FIN	FRA	ITA	NLD	PRT
Type of work	.037	.040	.066	.107	.090	.050	.088	.089
	(.06)	(.06)	(.03)	(.04)	(.04)	(.05)	(.04)	(.05)
Working conditions	.046	.038	−.011	.004	.066	.009	−.117	.093
	(.04)	(.06)	(.03)	(.03)	(.04)	(.03)	(.05)	(.05)
Working times	−.005	.095	.043	.048	−.070	−.016	−.034	−.023
	(.06)	(.04)	(.02)	(.04)	(.04)	(.03)	(.05)	(.04)
Distance to work	−.010	−.102	−.042	−.031	−.047	−.114	−.058	.142
	(.05)	(.06)	(.02)	(.04)	(.03)	(.03)	(.04)	(.05)
Job security	.132	.033	.022	.068	.075	.135	.073	−.012
	(.05)	(.05)	(.02)	(.04)	(.04)	(.04)	(.04)	(.05)

Table 5: Compensating differentials in the steady-state distribution

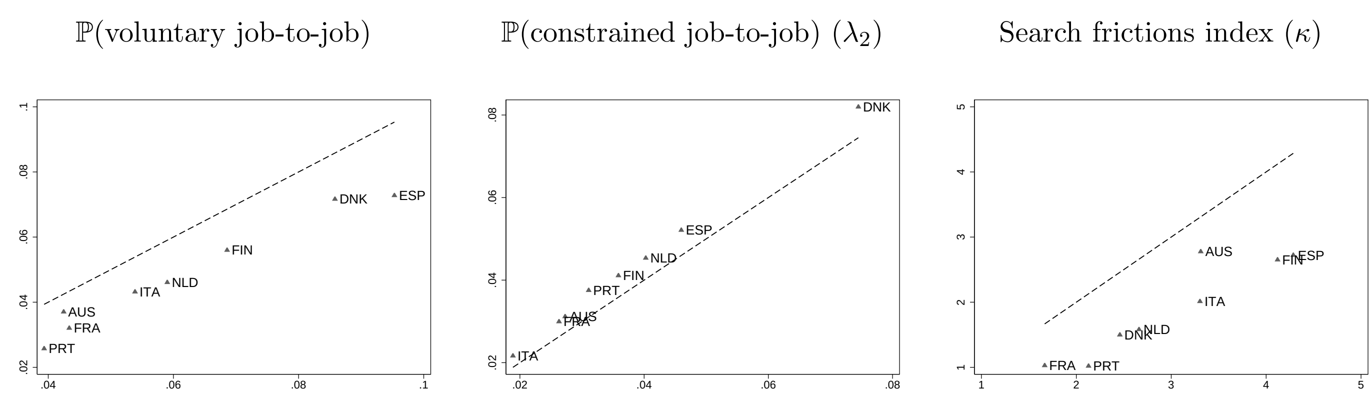
$\boldsymbol{\kappa = 30}$

	AUS	DNK	ESP	FIN	FRA	ITA	NLD	PRT
Type of work	-.001	.005	.041	.099	.092	.015	.051	.039
Working conditions	.037	.003	-.014	-.008	.086	.047	-.101	.128
Working times	.013	.079	.035	.063	-.124	-.026	-.038	.016
Distance to work	-.002	-.132	-.062	-.037	-.093	-.101	-.060	-.121
Job security	.101	.023	-.069	.032	.006	-.002	.046	-.220

Table 6: Compensating differentials posterior to a job change

	AUS	DNK	ESP	FIN	FRA	ITA	NLD	PRT
Type of work	.053	.060	.096	.090	.069	.048	.106	.082
	(.06)	(.06)	(.03)	(.04)	(.04)	(.04)	(.04)	(.05)
Working conditions	.043	.034	−.001	.027	.091	.012	−.115	.109
	(.04)	(.05)	(.02)	(.03)	(.04)	(.03)	(.05)	(.05)
Working times	−.009	.109	.038	.018	−.029	−.031	−.020	−.038
	(.06)	(.05)	(.02)	(.04)	(.04)	(.03)	(.05)	(.05)
Distance to work	.001	−.079	−.038	−.028	−.030	−.118	−.015	−.145
	(.05)	(.05)	(.02)	(.04)	(.04)	(.03)	(.04)	(.04)
Job security	.155	.085	.071	.119	.079	.157	.110	.046
	(.05)	(.05)	(.02)	(.04)	(.03)	(.03)	(.04)	(.05)

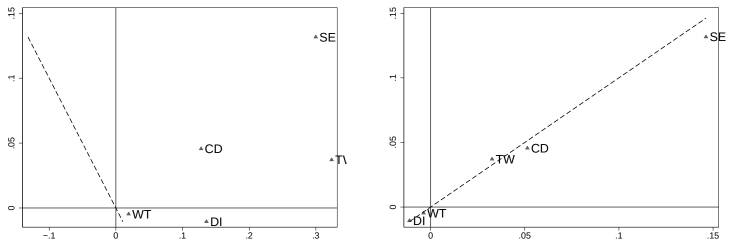
Figure 1: Job-to-job mobility and search frictions when amenities enter/do not enter worker's utility function.



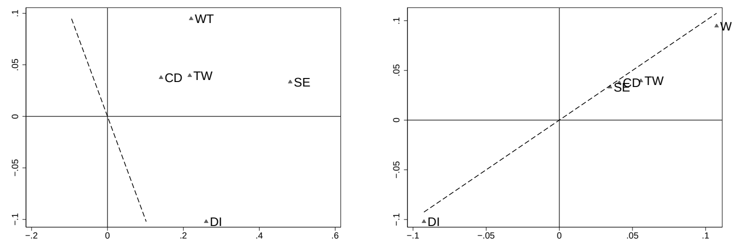
y-axis: estimates when MWP parameters are set to zero; x-axis: estimates from the unrestricted model.

Figure 2: Compensating wage differentials Δ in the steady-state distribution

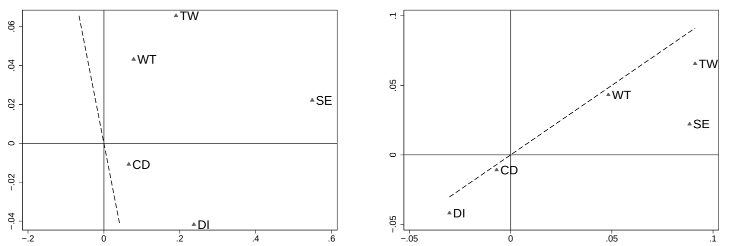
Austria



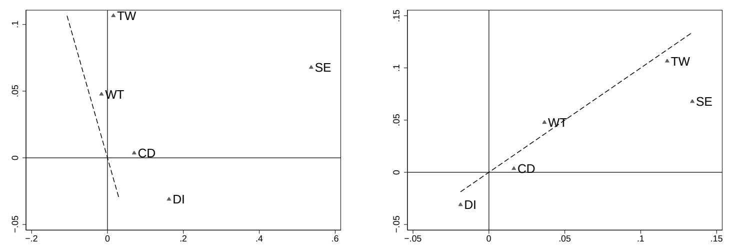
Denmark



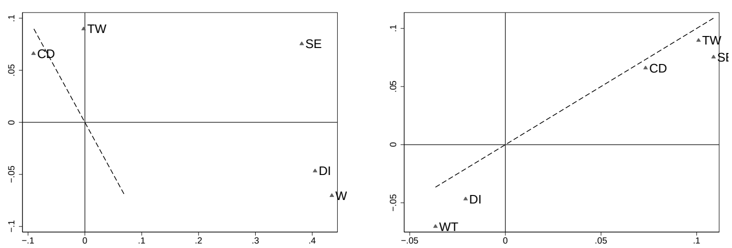
Spain



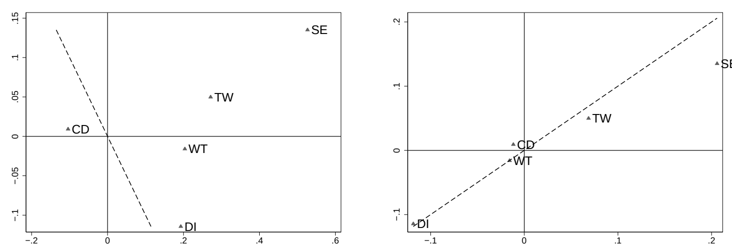
Finland



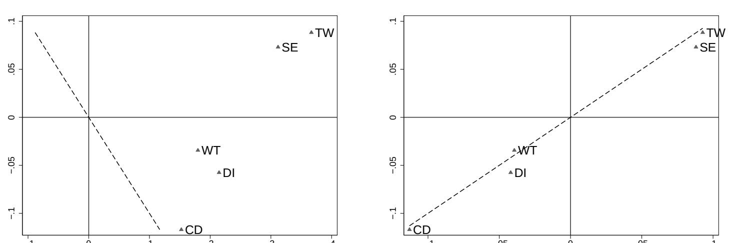
France



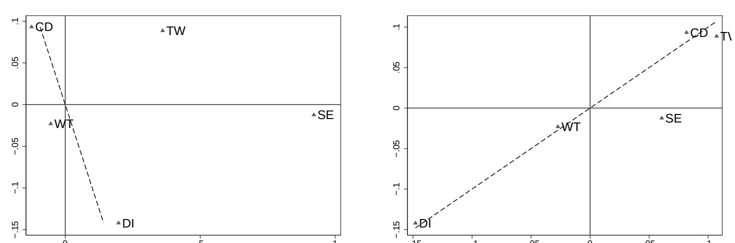
Italy



Netherlands

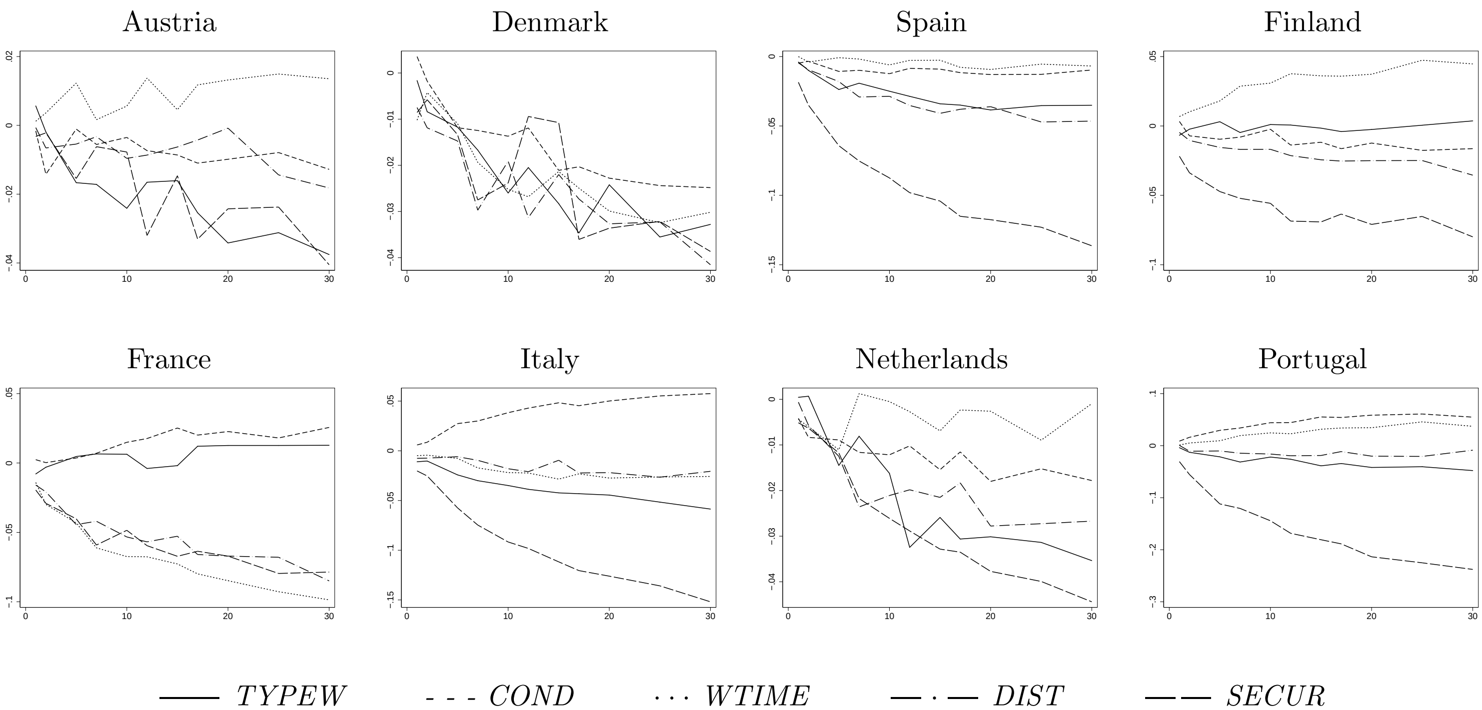


Portugal



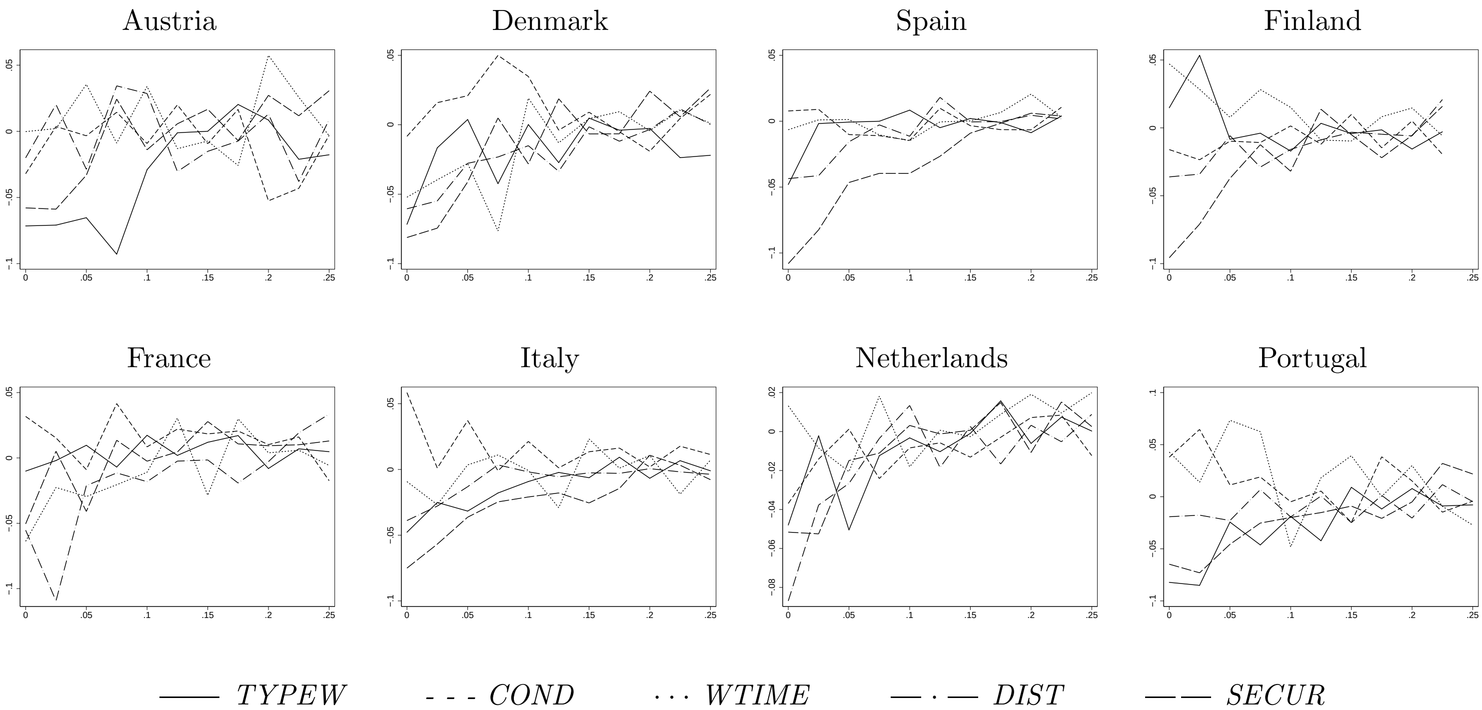
For each country: wage differentials Δ (y-axis) vs. MWP parameters δ (x-axis) on the left, and Δ (y-axis) vs. correlation in wage/amenity offers ρ (x-axis) on the right.

Figure 3: The effect of search frictions on compensating wage differentials, $\rho = 0$



Wage differentials Δ (y-axis) vs. search frictions index κ (x-axis).

Figure 4: The effect of λ_2/λ_1 on compensating wage differentials, $\rho = 0$



Wage differentials Δ (y-axis) vs. ratio of constrained to voluntary transitions λ_2/λ_1 (x-axis).

APPENDIX

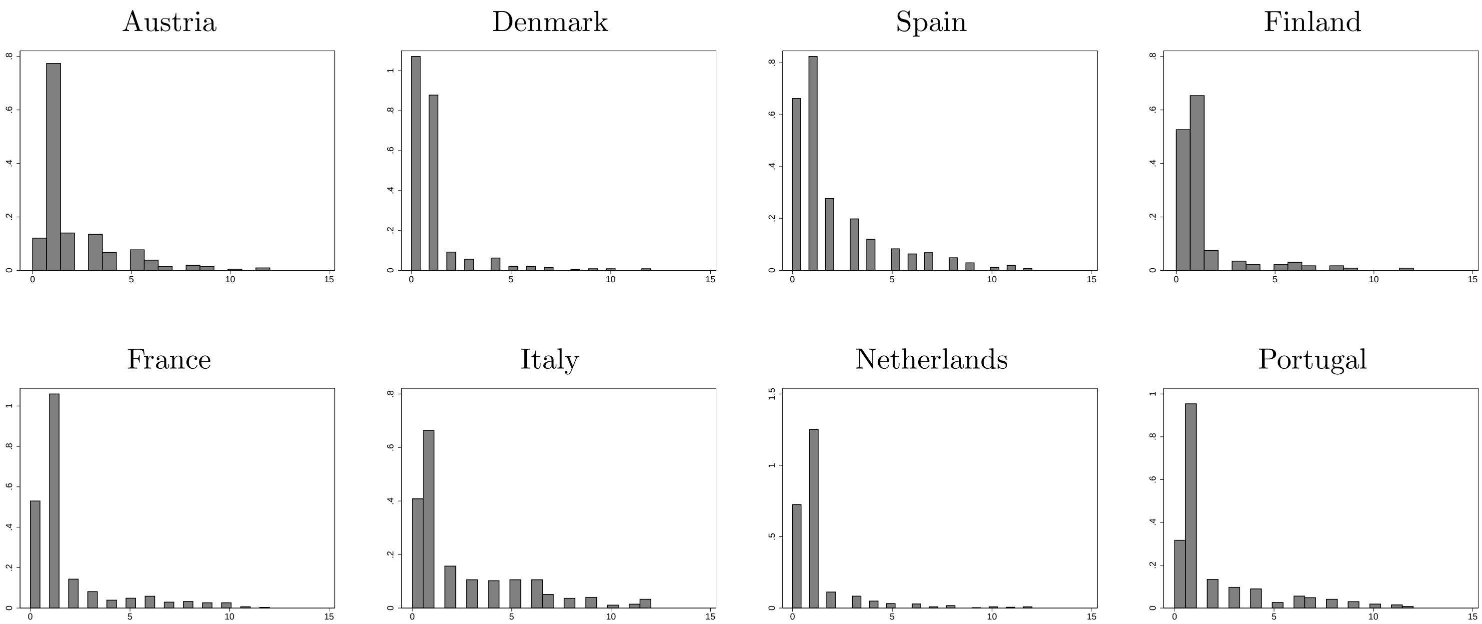
A Job-to-job mobility and time aggregation issues

The model allows for two types of job-to-job mobility. Since there are constrained job reallocations, as opposed to what is usually assumed in on-the-job search models, not all job changes are voluntary and increase utility. These job reallocations can have three sources: *i*) they can be due to actual constrained job changes for which workers found a new job before their previous one got terminated (for instance during the notice period); *ii*) they can actually be utility increasing but we are missing several unobserved dimensions of the job that enter workers' utility functions; or *iii*) they can arise from a time aggregation problem. The first source *i*) is a real economic motivation for introducing reallocation shocks, either in a discrete or in a continuous time setup. The other two sources, *ii*) and *iii*), result from data limitations. We refer the reader interested in *ii*) to the recent developments in the job search literature (Postel-Vinay and Robin, 2002, Burdett and Coles, 2003, and Dey and Flinn, 2005) for an analysis of other dimensions than the ones we study that can explain (voluntary) job changes. In this section, we take a close look at *iii*).

The time aggregation issue *iii*) is most problematic as the empirical definition of a job-to-job transition depends on the frequency of our panel data. As mentioned in section 3, the ECHP is a yearly panel so one can claim that a worker who is in different jobs at years t and $t+1$ might not have experienced a job-to-job transition but has actually transited through non employment for a period so short that we cannot observe it in our data. The only convincing way to address this issue would be to re-estimate the model on a panel with a higher frequency. At each year t, respondents of the ECHP are asked when (i.e. at which month) their previous job ended and when their current job started. These two variables can help us track individuals between two yearly interviews but, unfortunately, they do not allow us to recover the whole trajectory between t and $t+1$ and thus to build a monthly panel. Still, for those who have actually responded and changed job between two consecutive years, we can look at the distribution of the time elapsed between the end of the previous job and the start of the new one.

Figure A1 reveals that the vast majority of what we interpret as job-to-job transitions goes with zero or one month elapsed between the new job and the previous one. While this evidence does not solve the time aggregation issue completely (i.e. we cannot rule out job and non employment spells shorter than a month and/or workers can have more than two jobs during the year), it clearly does not lead us to reject our approach to job-to-job mobility.

Figure A1: Distribution of elapsed time (in months) between two jobs, conditional on changing job



B Consistency of the estimator

B.1 No unobserved heterogeneity

Let us denote as $\widehat{\lambda}$ and $\widehat{\delta}$ the numerical limits of $\widehat{\lambda}^{(s)}$ and $\widehat{\delta}^{(s)}$, respectively, when s tends to infinity. Together with $\widehat{\theta}$, they simultaneously satisfy the first-order conditions:

$$\begin{array}{lcl} \sum_{i=1}^{N}\sum_{t=t_0}^{T-1}\frac{\partial \ln f_{1,i,t+1}(\widehat{\theta})}{\partial\theta} & = & 0,\\ \sum_{i=1}^{N}\sum_{t=t_0}^{T-1}\frac{\partial\left\{\ln f_{2,i,t+1}\left(\widehat{\theta},\widehat{\lambda},\widehat{\delta}\right)+\ln f_{3,i,t+1}\left(\widehat{\theta},\widehat{\lambda},\widehat{\delta}\right)\right\}}{\partial\lambda} & = & 0,\\ \sum_{i=1}^{N}\sum_{t=t_0}^{T-1}\frac{\partial \ln f_{2,i,t+1}\left(\widehat{\theta},\widehat{\lambda},\widehat{\delta}\right)}{\partial\delta} & = & 0. \end{array}$$

Denoting as $\theta_\infty, \lambda_\infty, \delta_\infty$ the plim of $\widehat{\theta}, \widehat{\lambda}, \widehat{\delta}$ we have, taking plims:

$$\begin{array}{lcl} \mathbb{E}\left[\sum_{t=t_0}^{T-1}\frac{\partial \ln f_{1,i,t+1}(\theta_\infty)}{\partial\theta}\right] & = & 0,\\ \mathbb{E}\left[\sum_{t=t_0}^{T-1}\frac{\partial\{\ln f_{2,i,t+1}(\theta_\infty,\lambda_\infty,\delta_\infty)+\ln f_{3,i,t+1}(\theta_\infty,\lambda_\infty,\delta_\infty)\}}{\partial\lambda}\right] & = & 0,\\ \mathbb{E}\left[\sum_{t=t_0}^{T-1}\frac{\partial \ln f_{2,i,t+1}(\theta_\infty,\lambda_\infty,\delta_\infty)}{\partial\delta}\right] & = & 0. \end{array}$$

It is immediate to verify that, for all values of $\theta_a, \theta_b, \theta_c, \lambda_b, \lambda_c, \delta_b, \delta_c$:

$$\int \prod_{t=t_0}^{T-1} f_{1,i,t+1}(\theta_a) f_{2,i,t+1}(\theta_b, \lambda_b, \delta_b) f_{3,i,t+1}(\theta_c, \lambda_c, \delta_c) d\mu = 1,$$

where the integral is taken over the joint support of $(y_{t_0+1}, a_{t_0+1}, ...)$. So, the likelihood is a *partial likelihood* in the sense of Cox (1975). Letting $\theta_0, \lambda_0, \delta_0$ be the true values of the model's parameters we obtain, using straightforward calculus:

$$\begin{array}{lcl} \mathbb{E}\left[\sum_{t=t_0}^{T-1} \frac{\partial \ln f_{1,i,t+1}(\theta_0)}{\partial \theta}\right] & = & 0, \\ \mathbb{E}\left[\sum_{t=t_0}^{T-1} \frac{\partial \{\ln f_{2,i,t+1}(\theta_0,\lambda_0,\delta_0)+\ln f_{3,i,t+1}(\theta_0,\lambda_0,\delta_0)\}}{\partial \lambda}\right] & = & 0, \\ \mathbb{E}\left[\sum_{t=t_0}^{T-1} \frac{\partial \ln f_{2,i,t+1}(\theta_0,\lambda_0,\delta_0)}{\partial \delta}\right] & = & 0. \end{array}$$

Provided that this system uniquely identifies the parameters, it follows that $\theta_\infty = \theta_0$, $\lambda_\infty = \lambda_0$, $\delta_\infty = \delta_0$.

In addition, the characterization of the estimator as the solution of a just-identified set of moment equations shows asymptotic normality. The asymptotic variance-covariance matrix is given by the usual "sandwich" formula.

B.2 With unobserved heterogeneity

When s tends to infinity:

$$\begin{array}{lcl} \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \int \pi(z|y_i) \frac{\partial \ln f_{1,i,t+1}\left(\widehat{\theta}|z\right)}{\partial \theta} dz & = & 0, \\ \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \int \pi(z|y_i) \frac{\partial \ln\left\{ f_{2,i,t+1}\left(\widehat{\theta},\widehat{\lambda},\widehat{\delta}|z\right) f_{3,i,t+1}\left(\widehat{\theta},\widehat{\lambda},\widehat{\delta}|z\right)\right\}}{\partial \lambda} dz & = & 0, \\ \sum_{i=1}^{N} \sum_{t=t_0}^{T-1} \int \pi(z|y_i) \frac{\partial \ln f_{2,i,t+1}\left(\widehat{\theta},\widehat{\lambda},\widehat{\delta}|z\right)}{\partial \delta} dz & = & 0, \end{array}$$

where:

$$\pi(z|y_i) \equiv \pi(z|y_i; \widehat{\theta}, \widehat{\lambda}, \widehat{\delta}) = \frac{\pi(z) L_i\left(\widehat{\theta}, \widehat{\lambda}, \widehat{\delta}|z\right)}{\int \pi(\widetilde{z}) L_i\left(\widehat{\theta}, \widehat{\lambda}, \widehat{\delta}|\widetilde{z}\right) d\widetilde{z}}.$$

Taking plims we have:

$$\begin{array}{lcl} \mathbb{E}\left[\sum_{t=t_0}^{T-1} \int \pi_\infty(z|y_i) \frac{\partial \ln f_{1,i,t+1}(\theta_\infty|z)}{\partial \theta} dz\right] & = & 0, \\ \mathbb{E}\left[\sum_{t=t_0}^{T-1} \int \pi_\infty(z|y_i) \frac{\partial \ln\{f_{2,i,t+1}(\theta_\infty,\lambda_\infty,\delta_\infty|z) f_{3,i,t+1}(\theta_\infty,\lambda_\infty,\delta_\infty|z)\}}{\partial \lambda} dz\right] & = & 0, \\ \mathbb{E}\left[\sum_{t=t_0}^{T-1} \int \pi_\infty(z|y_i) \frac{\partial \ln f_{2,i,t+1}(\theta_\infty,\lambda_\infty,\delta_\infty|z)}{\partial \delta} dz\right] & = & 0, \end{array}$$

where:

$$\pi_\infty(z|y_i) \equiv \pi(z|y_i; \theta_\infty, \lambda_\infty, \delta_\infty) = \frac{\pi(z) L_i\left(\theta_\infty, \lambda_\infty, \delta_\infty|z\right)}{\int \pi(\widetilde{z}) L_i\left(\theta_\infty, \lambda_\infty, \delta_\infty|\widetilde{z}\right) d\widetilde{z}}.$$

Now, for similar reasons as in the previous paragraph, this system of equations is also satisfied at true values. Likewise, consistency and asymptotic normality follow.

C Additional estimation results

Table C1: (Mean) wage/amenity correlation in job offers, ρ

	AUS	DNK	ESP	FIN	FRA	ITA	NLD	PRT
Type of work	.033	.056	.091	.117	.101	.069	.093	.107
	(.06)	(.06)	(.03)	(.04)	(.04)	(.05)	(.04)	(.05)
Working conditions	.051	.042	−.007	.016	.073	−.012	−.113	.082
	(.04)	(.06)	(.03)	(.03)	(.04)	(.03)	(.05)	(.05)
Working times	−.004	.108	.048	.037	−.037	−.016	−.039	−.027
	(.06)	(.04)	(.02)	(.04)	(.04)	(.03)	(.05)	(.04)
Distance to work	−.011	−.093	−.030	−.019	−.021	−.119	−.042	−.148
	(.05)	(.06)	(.02)	(.04)	(.03)	(.03)	(.04)	(.05)
Job security	.146	.035	.088	.134	.109	.206	.088	.061
	(.05)	(.05)	(.02)	(.04)	(.03)	(.04)	(.04)	(.05)

Due to a too small number of job entrants in Austria, we could not estimate ρ as a function of observed characteristics x. Hence, only for this country, we have modelled ρ as a constant parameter.