

## LOOKING FOR LABOUR MARKET RENTS WITH SUBJECTIVE DATA

**Andrew E. Clark**  
(CNRS and DELTA)

**September 2003**

### ABSTRACT

A long-running debate in labour economics concerns the interpretation of industry and occupational wage differentials. One view is that these reflect compensating differentials for mostly unmeasured aspects of jobs: **utilities** are equalised between industries and occupations, but **wages** are not. Alternatively, there may be labour market rents: identical workers in some industries and occupations have better jobs (as in higher utility) than do others. This paper proposes a trick by which it is not necessary to measure job disamenities in order to test for the presence of rents. The correlation between the estimated 2-digit occupation coefficients from wage and job satisfaction regressions is examined. If wage differentials are rents, then “high-paying” occupations should also be “high satisfaction”. If wage differences are purely compensating differentials then no relationship should be found. An analogous approach is taken for industry dummies.

Using eleven waves of British panel data, it is shown that there is a persistent positive and significant correlation between the estimated occupational dummies, but no relation between the industry dummies, both in level and panel regressions. Analysis of spell data shows that high-rent occupations are reached through promotion, rather than worker-induced mobility, suggesting the existence of tournaments within firms. Last, I show that high wage rent occupations are also high social status (as defined by recent sociological research), whereas status has no relation with the non-rent part of wages.

JEL Codes: C30, J28, J31, J41, M51.

---

Address: DELTA, 48 Boulevard Jourdan, 75014 Paris, France. Tel: 33-1-43-13-63-29. E-mail: [Andrew.Clark@ens.fr](mailto:Andrew.Clark@ens.fr). DELTA is a joint research unit of the CNRS, the EHESS and the ENS.

# LOOKING FOR LABOUR MARKET RENTS WITH SUBJECTIVE DATA

Andrew E. Clark\*

## 1. Introduction

A long-running debate in labour economics concerns the interpretation of industry and occupational wage differentials. Broadly, two opposing interpretations have been presented. One is that these are compensating differentials representing unmeasured aspects of jobs which are not evenly distributed over industries and occupations. According to this view, while utilities are equalised between industries and occupations, wages are not. Consequently, if all relevant right-hand side variables could be adequately measured, no such differentials would be found.

A second interpretation contends that there are rents in the labour market, and that workers in some industries and occupations really do enjoy better jobs (as in higher utility) than do others.

This paper takes a novel approach to this old question by using job satisfaction data as a proxy measure of utility at work. It asks whether those individuals who are identified as being in “high wage” industries and occupations according to a wage equation are equally in “high satisfaction” industries according to a job satisfaction equation. If wage differences do no more than compensate for disutilities, then there is no reason to expect that high wage industries/occupations will also exhibit high job satisfaction. On the other hand, if there are rents in the labour market, then high wages and high job satisfaction should go together.

This hypothesis is tested on nine waves of British panel data, which contain rich demographic and job data, and measures of job satisfaction. A two-stage procedure is employed. Two-digit industry and occupation dummies are introduced into wage equations to pick up systematic wage variations that are not captured by the other controls. The same set of explanatory variables are then used in an ordered probit equation to model job satisfaction.

In the second stage, I examine the correlation between the estimated occupation coefficients from the wage equation and their counterparts from the job satisfaction equation. As the metric of these two sets of estimated coefficients is not the same, I calculate Spearman rank correlation coefficients. To control for the precision of the estimated coefficients, I also consider the relationship between the estimated t-statistics. An analogous procedure is followed for the industry coefficients. The results are striking. High-wage occupations are indeed high satisfaction occupations: the correlations are particularly strong for younger workers and for men. However, there is little evidence that the pattern of wages between industries, *ceteris paribus*, is related to the pattern of job satisfaction between industries. Similar results are found in panel regressions which control for unobserved individual heterogeneity.

A natural interpretation is that occupational wage differentials are at least partly rents, whereas those at the industry level reflect compensating differentials. There are, of course, rival explanations, based on individual heterogeneity. Individuals may have different tastes for wages or for job disamenities. In this case it is likely that those who value income more and/or dislike hard work less will flock to high-wage difficult jobs: the choice of occupation becomes endogenous. The equilibrium is competitive, in that no workers with low-wage low-difficulty jobs would be prepared to swap them for high-wage high-difficulty jobs.

No information is available on workers' tastes. Inasmuch as these tastes are fixed, they will be controlled for in the panel regressions. These latter yield similar results to level regressions, again suggesting that there are rents. A counter-argument is that such sorting as described above takes time, and the panel regressions are picking up exactly this adjustment. However, if this is the case, we would expect to see larger correlations between wages and job satisfaction for older workers, whereas we observe the opposite in the level regressions. Last, an attempt has been made to control explicitly for individual preferences. Marital status, number

and ages of children, partner's labour force status and partner's income may all be thought to influence the marginal utility of own income. Parents' labour force status and parents' two-digit occupational codes (both measured when the respondent was aged 14) may well be correlated with the individual's taste for different types of jobs. All of these variables are added to the first-stage wage and job satisfaction regressions. Their inclusion in no way changes the paper's principal result: that wage and job satisfaction residuals are correlated by occupation but not by industry.

The paper is organised as follows. Section 2 briefly summarises the two equations to be estimated, and Section 3 presents the data. Section 4 contains the main regression results, and presents some interpretations. Section 5 concludes.

## 2. Wage and Job Satisfaction Equations

The empirical debate has been bedevilled by a lack of suitable data, measuring all important characteristics of a job across sectors in order to ensure the *ceteris paribus* assumption. This lacuna is likely to persist, as many important characteristics of a job are difficult to quantify or even to observe (Clark, 1998).

This paper proposes one obvious way of overcoming this lack of suitable variables: find another variable which is strongly correlated with them. Job satisfaction is suggested to present a viable measure of the utility associated with working. As such, it includes information about a wide variety of job characteristics which workers find important but the average applied labour economist has no hope of measuring. Such measures have been repeatedly shown to be a good measure of how a worker feels about his or her job, in that it is a strong predictor of workers' future behaviour (quits, productivity, absenteeism), and often a stronger predictor of quits than are objective variables (wages and hours of work) that labour economists typically model.

The approach taken in this paper to distinguish between the compensating differential and rent interpretations can be illustrated with the help of simple wage and utility functions. The wage of worker  $i$  in occupation  $o$  is argued to depend on a raft of individual and job characteristics,  $X_i$ , compensation for the disamenities in that occupation,  $D_o$ , and an occupation specific rent,  $\alpha_o$ :

$$w_{io} = \psi'X_i + \alpha_o + \beta D_o \quad (1)$$

This assumes, for simplicity, common disutility compensation across occupations.

The utility function of the same worker,  $U_{io}$ , is assumed to be linear in wages and job disamenities, and to depend (for simplicity) on the same  $X$ 's as do wages in (1):

$$U_{io} = \lambda'X_i + \phi w_{io} - \gamma D_o \quad (2)$$

The compensating differential offered by the market for  $D_o$  will be just enough to keep the worker on the same indifference curve. Considering  $D_o$  as a binary variable, the market will therefore provide compensation of  $\beta = \gamma/\phi$ .

Substituting (1) in (2) yields

$$U_{io} = \theta'X_i + \phi\alpha_o \quad (3)$$

Neither rents nor disamenities can be directly measured. In empirical analysis they will be picked up by the estimated coefficients on the occupation dummies. This paper's strategy is therefore to estimate equations (1) and (3) with the addition of two-digit occupational variables. In the wage equation, the estimated coefficients on these dummies will pick up both rents and disamenities. However, in a utility equation (here proxied by overall job satisfaction), when wage is not controlled for these dummies will only reflect rents.

The empirical strategy is therefore to see if the systematic differences in utility/job satisfaction across occupations are correlated with their counterparts in a standard wage equation: Are workers in occupations where wages are inexplicably higher also inexplicably

more satisfied with their jobs? In terms of equations (1) and (3), this amounts to correlating the estimate of  $\alpha_o + \beta D_o$  with that of  $\varphi\alpha_o$ . If these two are indeed strongly correlated, then we may conclude that the rent component of wage differentials ( $\alpha_o$ ) is substantial. On the other hand, if the rent element is small, then the correlation between  $\alpha_o + \beta D_o$  and  $\varphi\alpha_o$  will also be small<sup>1</sup>.

### 3. Data

The current paper uses data from the first nine waves of the British Household Panel Survey (BHPS), a general survey covering a random sample of approximately 10 000 individuals in 5 500 British households per year. This data set includes a wide range of information about individual and household demographics, health, labour force status, employment and values. There is both entry into and exit from the panel, leading to unbalanced data. The BHPS is a household panel: all adults in the same household are interviewed separately. The wave 1 data were collected in late 1991 - early 1992, the wave 2 data were collected in late 1992 - early 1993, and so on.

There are just under 45 000 observations with non-missing wage and job satisfaction information, concerning 12 000 different individuals. Dropping observations with missing values for the right-hand side variables used in the subsequent regressions yields a final sample of 30 600 observations on 7 800 different individuals.

The key question used in this paper is that regarding job satisfaction, which is taken as a proxy measure of utility at work. Job satisfaction has been shown to be a useful predictor of various work-related behaviours, such as quits (Freeman, 1978, Clark, Georgellis and Sanfey, 1998, and Clark, 2001), absenteeism (Clegg, 1983) and productivity (Mangione and Quinn, 1975, and Patterson *et al.*, 1997). As such, it seems to be a viable index of the work-related component of utility.

In the BHPS data, respondents in employment initially rate their satisfaction levels with seven specific facets of their job (promotion prospects, total pay, relations with supervisors, job security, ability to work on one's own initiative, the actual work itself, and hours of work), each of which was to be given a number from one to seven, where a value of one corresponded to "not satisfied at all" and a value of seven corresponded to "completely satisfied". After they had rated their levels of contentment with the list of topics, individuals were asked a final question, worded as:

*"All things considered, how satisfied or dissatisfied are you with your present job overall using the same 1-7 scale?"*

It is the response to this last summary question which is used as a proxy measure of utility at work. The distribution of overall job satisfaction for this sample is shown below. As is typically found, there is bunching towards the top of the scale. Both the median and modal response is 6, on the 1 to 7 scale, and only 12% of respondents give responses of less than 4.

<b>Overall Job Satisfaction</b>			
	<i>Value</i>	<i>Frequency</i>	<i>Percentage</i>
Not Satisfied at All	1	521	1.9%
	2	772	2.9%
	3	1966	7.3%
	4	2177	8.1%
	5	5718	21.3%
	6	11595	43.2%
Completely Satisfied	7	4088	15.2%
Total		----- 26837	----- 100.0%

In the empirical analysis, the first three job satisfaction categories will be recoded together. The following section presents the results of wage and job satisfaction regressions. The focus will be firmly on the relationship between the estimated occupation (and industry) coefficients in

these two regressions.

#### 4. Main Regression Results

A very wide range of control variables are used in the wage and job satisfaction regressions in equations (1) and (3) respectively. The latter is estimated using ordered probit techniques. In the first instance both are estimated on pooled data, using Huber-White techniques to correct the standard errors for correlation at the individual level. In addition to industry and occupation, the regressions control for demographic variables (region, wave, age, race, sex, education, health, marital status and house-renter) and job variables (hours, union member, union recognition, temporary job, manager, tenure, firm size, promotion opportunities, whether a second job is held, organisation type, work times, incentive schemes, and pension schemes). Last, I control for the local unemployment rate (matched in from Labour Force Survey data), which is typically negatively correlated with wages (Blanchflower and Oswald, 1995) and (to a perhaps lesser extent) with workers' well-being (Clark, 2003). As equation (3) makes clear, job satisfaction is estimated here without controlling for the wage (it is the variation in the wage which is supposed to cancel out the presence of job amenities or disutilities in the compensating differential set-up).

In all of the empirical work presented in the paper, the omitted industry and occupation group is that with the largest number of observations. In addition, results are not presented for cells with fewer than twenty observations, these observations being dropped. This yields, in the pooled results, 53 two-digit industry categories and 75 two-digit occupation categories, with somewhat fewer in the panel analysis and the sub-regressions.

#### *Main Results*

The first two columns of Table 1 presents the results of wage and job satisfaction



regressions using pooled data. The wage regression explains over 80% of the variation in wages in the sample. The wage results are typical of those found in the literature. Wages are convex in age and tenure, and are higher for men, the better-educated, those in better health, the married, those in larger firms, and union members. The job satisfaction regression also reveals some correlations that are relatively well-known in the small empirical literature (see Clark, 1996). Job satisfaction is U-shaped in age (Clark *et al.*, 1996), is lower for males (Clark, 1997), the better-educated, union members, and those in larger firms, but higher for the married and those in better health.

Columns 3 and 4 of Table 1 present analogous results using panel estimation techniques. Column 3 estimates wages via a “within” regression, and in column 4 a fixed effect logit is used to estimate the probability of being “highly satisfied” (job satisfaction of six or seven on the one to seven scale). The panel regression results are very similar to those from the pooled regressions in the first two columns.

Of most interest in these regressions are the estimated coefficients on the industry and occupational dummies (53 and 75 respectively) across the two regressions. If wage differentials are (partly) rents, then we would expect workers in industries and occupations which pay well to also be relatively more satisfied with their jobs. In Table 1's level results, 20 out of the 75 occupational coefficients (27%) are of the same sign and significant in both the wage and job satisfaction equations, as compared to only 2 out of the 53 industry coefficients (4%).

Table 2 presents formal correlation results using both robust regression techniques (to control for undue influence of outliers when there are only a relatively small number of observations) and Spearman rank correlation statistics. As the correlations here are between constructed variables, rather than between data, I bootstrap the correlations, with one thousand replications.

Table 2 presents, in the first and third columns, estimated t-statistics for the robust regression of the occupational (or industrial) wage residual on the occupational (or industrial) job satisfaction residual. The second and fourth columns show the analogous estimated rank correlation coefficients. Bold figures are significant at the five per cent level, and italic figures are significant at the ten per cent level. Two rows are presented within each panel. The first shows the correlation between the estimated wage occupation/industry coefficients and their job satisfaction counterparts. It may, however, be argued that estimated coefficients may be large but imprecisely estimated. One way of overcoming this criticism is to weight each observation by the inverse of its standard error, so that better-defined estimates have greater weight. This amounts to correlating the t-statistics, which is the second measure.

The contrast between the industry and occupation results in Table 2 is striking. Strong correlations, especially for the t-statistics, are found for the estimated coefficients on the occupation dummies. On the contrary, there is little evidence that industries with high wages are also industries with highly satisfied workers<sup>2</sup>. These results hold for both level and panel regressions<sup>3</sup>. One interpretation is that at least part of occupational wage differentials represent rents: workers who are paid more than we, as econometricians, would expect, also record higher job satisfaction scores than we would expect<sup>4</sup>. However, industries with highly-paid workers are not industries with highly-satisfied workers.

#### *Sub-regressions*

As with most labour market phenomena, it is of interest to ask which groups are most affected. The remainder of Table 2 presents rank correlation coefficients by various demographic and job variables (Sex, age, education and public/private sector<sup>5</sup>). No positive significant correlations between industry wage and job satisfaction coefficients are found in any of the sub-groups. On the contrary, the occupation results show a number of strong correlations: workers

in high-wage occupations are more satisfied with their jobs. This correlation is particularly strong for younger workers (under the age of 40) and men. There is also weaker evidence that the correlation is higher (and hence, according to this paper's interpretation, that rents are more important) for higher-educated workers<sup>6</sup>.

Figure 1 provides a graphical illustration of the second stage, showing the estimated industry and occupation coefficients and industry and occupation t-statistics for men. The points are weighted by the number of observations in each industry or occupational group. At the occupational level, both the estimated coefficients and the associated t-statistics are clearly positively correlated. Over 80 per cent of the points are in the NE or SW quadrants, and 22 of the 68 observations<sup>7</sup> (32%) consist of t-statistics which both reflect significance at the five per cent level and which are of the same sign. By way of contrast, none of the 52 industry points satisfy this criterion.

## 5. Interpretation of the Results

The conclusion from Section 4 is that industries which pay well do not have workers who are any better satisfied than those in other industries. On the contrary, high-paying occupations are associated with more satisfied workers. A provisional conclusion, in line with the paper's hypothesis, is that occupational wage differentials are partly rents, whereas higher industry wages do not induce higher satisfaction and may therefore be considered as compensation for job disamenities (either physical working conditions, or payment for higher effort in an efficiency wage framework)<sup>8</sup>.

This section will initially consider some alternative explanations of the correlation between wages and job satisfaction at the occupational level, before using spell data from the BHPS to shed some light on how workers get to the supposed "high-rent" jobs.

*i) Specific Human Capital, and Other Omitted Variables*

An obvious worry regarding the above results is that there are omitted variables which are correlated with both wages and job satisfaction. One candidate is ability (see Gibbons and Katz, 1992). However, to the extent that ability is fixed, it will be washed out in the panel regressions, which nevertheless in Table 2 exhibit the same qualitative results as in the level regressions. This argument equally applies to any other omitted variable which is fixed over time. As a further check, was introduced in place of the coarse three-level variable in Table 1. This in no way changed the results. It should be noted that Table 1 includes a relatively fine thirteen-level education variable, as well as controls for both tenure and its square, which will pick up learning by doing.

*ii) Heterogeneity in preferences*

This point relies on the potential heterogeneity of workers in their tastes for hard work and income. Endogenous occupational choice suggests that those who are least harmed by hard work (or who have the highest marginal utility of income) may well choose difficult, high-paying jobs: the sorting of workers into job types could be behind the wage and job satisfaction correlations at the occupational levels (although it would remain to be explained why such sorting is not observed at the industry level).

A first general point is that any such fixed preferences will be controlled for in panel regressions, which however reveal the same correlation results as the level regressions. It can be countered that such sorting takes time, and it is exactly this that the panel results are picking up. However, in this case we might reasonably expect the correlations between occupational wage and job satisfaction residuals to be stronger for older workers, for whom such sorting is presumably completed. In fact Table 2 shows that the opposite is true: higher wages are associated with higher job satisfaction only for younger workers.

Nevertheless, an explicit test requires that tastes for income and hard work be controlled for in the first-stage regressions. My approach here has been to find variables that are arguably correlated with such tastes. With respect to job disamenities, I use dummy variables for whether the individual's father *a*) worked or not (when the respondent was aged 14), *b*) was self-employed, *c*) had employees, and *d*) was a manager; I also control for the father's occupation (at the one-digit level). Analogous variables are used for the respondent's mother. With respect to the marginal utility of income, I control for the number and ages of children, spouse's labour force status, and spouse's wage and hours of work.

A number of these variables attract significant estimates, although relatively few are of the same sign in the wage and job satisfaction regressions. The key finding is that their addition to the first-stage regressions in no way changes the correlations found in Table 2.

### *iii) Learning about ability*

The rough idea here is that individuals (and firms) don't know how productive they are in a match. After a certain time, productivity is revealed. Individuals are (un)happy if they find out that they are (un)productive, and individuals in the "best" matches will be promoted. This would describe the tenure track systems in many universities, for example. As opposed to explanations based on fixed unobservable human capital, this resolution of uncertainty is able to explain the panel results.

Again, direct tests are not available. However, two pieces of evidence may be used to counter this idea. The first is that there is no *a priori* reason why such "surprises" should be more prevalent at the occupational level than at the industry level (this criticism can equally be levelled at the human capital explanation). Second, there should be no correlation between wages and job satisfaction once uncertainty has been resolved. I therefore re-ran the main analysis on the sub-sample of workers who had been in the same job for over three years. The same

correlations were found in this “long tenure” sample, casting doubt on learning as an explanation for the correlations between occupational wages and job satisfaction.

*iv) Labour Market Transitions and Job ladders*

The last interpretation of this paper’s results maintains that part of occupational wage structure represents rents. As I hold that some occupations really are better than others, it is obvious to ask the question: How do individuals obtain these “good jobs”?<sup>9</sup> The BHPS data contains detailed labour market spell information, which I here use to provide some suggestions about how the British labour market works.

I limit this investigation to occupational differences, as it is here that supposed rents are found. I first split occupations up into two job satisfaction groups: “high” (20 occupations) and “not high” (55 occupations), using the estimated occupation coefficients from Table 1's level results (where “high” refers to occupations with positive significant coefficients, and “not high” to the others). I then use the dataset of labour market spells which is supplied with the BHPS data to see how individuals move into these different types of jobs.

The first part of Table 3 shows that individuals are more likely to move into good jobs if they were working in the previous labour market spell, which is perhaps unsurprising. The second panel looks at those who were employed in the previous labour market spell, and cuts up current job quality by the reason the previous job episode ended. The results show that it is promotion which leads to the good jobs: 45 per cent of promotees move into high-quality jobs, as opposed to only 32 per cent of those who “left for a better job”<sup>10</sup>. T-tests reveal that the percentage moving into high-quality jobs via promotion is greater than the percentage moving for any of the other reasons at far better than the 0.1 per cent level.

The figures to the right of this second panel show that the average changes in the

occupational wage and job satisfaction coefficients according to the reason that the last job spell ended. Again, it is promotees who enjoy both the largest rise in the occupational wage coefficient (the move towards “inexplicably” high-paying occupations) and the largest rise in the occupational job satisfaction coefficients (the move towards “inexplicably” high-satisfaction occupations).

The last panel presents transition matrices between the two levels of job quality, both for non-promotees and for promotees. It is the upper diagonal of these matrices which are of interest: those who increase the quality of their job. This figure is 16 per cent for non-promotees, but 22 per cent for promotees, a significant difference at the 0.1 per cent level.

The finding that it is the employed who move to good jobs is not surprising. What is perhaps more novel is that access to good jobs, defined here as those with high job satisfaction (and mostly high wages: see Table 2), is obtained through promotion. This may explain why rents are not competed away: it is not the worker who decides whether she is promoted, but the firm<sup>11</sup>. The question remains why firms would make rents available (via promotion) to workers. An answer is supplied by tournament theory: rents are available to the winners of tournaments, and this incites hard work. Although it is difficult to test tournament theory directly, I believe that the results in this paper show that, at the occupational level, high-wage occupations are indeed high-rent occupations. Access to these high-rent occupations seems to be determined by firms themselves, which suggests that it is in their interest that such rents remain<sup>12</sup>.

#### v) *Social Status and the Labour Market*

Although much has been written about social status and social class, objective measurement of such phenomena presents serious difficulties. One standard measure of social class is the Goldthorpe scale, which is calculated using labour market status. Some of Goldthorpe’s more recent work has created social status scores by looking at the occupational

structure of friendship in large scale survey data. Chan and Goldthorpe (2003a) uses wave 10 of the BHPS, which includes demographic information on the respondent's best friend, to create a rank order of 25 occupational groups (calculated from two-digit SOC information). This ranking, and the associated status scores from the multi-dimensional scaling technique employed, can be found in Table 2 of Chan and Goldthorpe (2003b).

Although a clear status ordering emerges from the analysis, it is less clear why some occupations are high- and some low-status. To shed some light on this fairly fundamental question, I calculated (using frequency weights) average wages using Chan and Goldthorpe's 25 classes. More specifically, I split wages up into three parts, using the results from the level wage equation in Table 1. First, the non-occupational part of wages: the predicted value from Table 1, but without the estimated occupation coefficient. Second, the occupational part of wages, as given by the estimated occupation coefficient. Third, the residual part of wages (*i.e.* orthogonal to all of the explanatory variables in the wage equation). Figure 2 shows the scatter of points between Chan and Goldthorpe's occupational status score and the three parts of wages. The estimated bivariate regression line is overlaid. The only correlation is between the occupational part of wages and social status. This conclusion is formalised in the bivariate and multivariate correlations in Table 4.

Chan and Goldthorpe make the point that status is not a synonym for income. Here I can go further. Occupational status does not seem to be correlated with the returns to human capital. However, occupations where wages are inexplicably high are high-status. In terms of the questions this paper has posed, capturing labour market rents confers social status.

## 6. Conclusion

This paper has used eleven waves of British panel data to show that high-wage



occupations are also high job satisfaction occupations. I suggest that this finding rejects a purely compensating differential interpretation of the occupational wage structure.

The relationship is found in both level and panel regressions, and is stronger for men and for younger workers. I argue that these findings are not consistent with explanations based on unobserved individual heterogeneity and the endogenous choice of occupations.

My preferred interpretation is in terms of occupational rents. An indication as to why these rents are not competed away comes from the analysis of the labour market episodes in the data. Movements to “good jobs” are significantly more likely to come via promotion than via quitting. Some simple analysis of transition matrices shows that promotees are significantly more likely to move up the job quality ladder than are those whose last job ended for any other reason. It therefore seems to be firms, rather than workers, who hold the key to what I argue are high-rent jobs, which explains why such rents are not competed away. This finding is consistent with tournament theory.

## Footnotes

\* I am grateful to Orley Ashenfelter, Giacomo Corneo, Fabrice Etilé, Claude Fluet, Paul Frijters, Olivier Godechot, Marc Gurgand, Jon Haisken-DeNew, Dan Hamermesh, Jean-Yves Lesueur, David Margolis, Jean-Marc Robin, Bob Sandy, Stan Siebert and Jeff Wooldridge for comments. I also thank seminar participants at the AEA Meetings (Atlanta), the EALE Conference (Paris), Evry, GATE, ISQOLS5 (Frankfurt), the First IZA/SOLE Transatlantic Labor Economics Conference, the Jourdan Labour Group, the 20<sup>th</sup> Journées de Microéconomie Appliquée (Montpellier), Paris 1, Paris 2, and the Tinbergen Institute. The BHPS data were made available through the ESRC Data Archive. The data were originally collected by the ESRC Research Centre on Micro-social Change at the University of Essex. Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here. This research benefitted from financial support from the ATIP programme of the CNRS.

1. Lalive (2002) is somewhat along the same lines. He uses the sub-sample of individuals with two jobs in the NLSY, who report two wage levels and two job satisfaction levels. He then correlates the wage difference between the two jobs with its job satisfaction counterpart. Kawaguchi (2003) implicitly uses the same approach as the current paper to consider whether the higher wages of the self-employed represent compensating differentials. Godechot and Gurgand compare the estimated coefficients on job disamenities in wage and job satisfaction equations. Alan Krueger (private communication) tells me that the first version of Krueger and Summers included job satisfaction data.

2. It may be countered that the wage and job satisfaction equations should be estimated jointly. Considering job satisfaction as cardinal, I re-estimated the level equations using Zellner's seemingly unrelated regression equations technique. The resulting t-statistics on the correlations between the estimated occupation coefficients in the two equations are if anything somewhat stronger. The correlations between estimated industry coefficients are all insignificant.

3. More prosaically, plotting the estimated coefficients in the wage and job satisfaction regressions against each other, sixty per cent of the occupation pairs are in the NE/SW quadrants, compared to only just over a quarter of the industry pairs.

4. It is worth remembering that, in a world of compensating differentials, there is no reason why job satisfaction should be higher in high-wage occupations. Indeed, at the industry level it isn't.

5. Sub-regressions by union status and by firm size produced no striking results.

6. Despite the much smaller sample sizes, the same qualitative results can be reproduced in sub-regressions using panel data techniques.

7. Seven additional two-digit occupations are dropped for men, as they contain less than twenty observations each.

8. A further test can be carried out to reinforce this interpretation. I matched in male serious injury rates at the two-digit occupational level. These were not significantly correlated with the estimated occupation coefficients from the job satisfaction equation. Further, in a simple OLS regression, controlling for injury rates did not change the strong significance of the correlation between the estimated occupation coefficients in the wage equation and the estimated occupation coefficients in the job satisfaction equation.

9. The “best” occupations, as measured by estimated coefficients in the job satisfaction regressions, are Health & related occupations, Health professionals, and Managers & administrators. The worst are Assemblers/lineworkers and Other routine process operatives.

10. As might be expected from Table 2, these differences are stronger for men. Here, for example, 36 percent of promotees move into high quality jobs, compared to only 24 per cent of voluntary quitters: the percentage point gap for men is twice as high as that in Table 3.

11. I had originally thought that the occupation coefficients in a quit equation would be correlated with those from the wage and job satisfaction equations in Table 1. This was not the case. Workers show no greater tendency to quit from low-wage/job satisfaction occupations. If their access to high-wage/satisfaction occupations is via promotion, then this is understandable.

12. It is of course impossible to appeal to tournaments to explain industry-wage differences, as firms generally operate in one industry only.

Table 1. Wage and Job Satisfaction Regressions.

	<u>Level Equations</u>		<u>Panel Regressions</u>	
	<i>Wages</i>	<i>Job Satisfaction</i>	<i>Wages</i>	<i>Job Satisfaction</i>
Age	0.045 (.003)	-0.048 (.007)	---	---
Age-squared/1000	-0.530 (.031)	0.666 (.087)	---	---
Male	0.173 (.014)	-0.198 (.041)	---	---
Education Dummies (13)	Yes	Yes	---	---
Regional Unemployment Rate	-0.006 (.003)	-0.001 (.009)	0.000 (.002)	-0.011 (.022)
Union member	0.036 (.009)	-0.092 (.026)	0.039 (.008)	-0.075 (.088)
Temporary contract	-0.072 (.014)	-0.153 (.038)	-0.076 (.009)	-0.117 (.103)
Ethnic group: African/Caribbean	-0.048 (.038)	-0.263 (.094)	---	---
Ethnic Group: Indian Subcontinent	-0.062 (.032)	0.056 (.09)	---	---
Health: Excellent	0.031 (.009)	0.372 (.026)	0.003 (.006)	0.421 (.073)
Health: Good	0.014 (.007)	0.152 (.022)	0.002 (.005)	0.228 (.058)
Manager/Supervisor	0.125 (.007)	0.031 (.022)	0.064 (.005)	0.049 (.06)
Log hours	0.846 (.015)	-0.292 (.032)	0.702 (.008)	-0.474 (.104)
Married	0.039 (.01)	0.158 (.031)	0.054 (.01)	-0.245 (.116)
Separated	0.023 (.02)	0.127 (.071)	0.051 (.018)	0.047 (.207)
Divorced	0.019 (.017)	0.111 (.047)	0.060 (.016)	-0.369 (.185)
Widowed	0.013 (.03)	0.317 (.111)	0.042 (.039)	0.569 (.485)
Job Tenure	0.035 (.011)	-0.140 (.042)	0.013 (.008)	-0.999 (.115)
Job Tenure Squared	-0.001 (0)	0.003 (.002)	0.000 (0)	0.017 (.005)
Firm Size: 1-24	-0.116 (.01)	0.180 (.027)	-0.052 (.007)	0.105 (.078)
Firm Size: 25-199	-0.028 (.008)	0.059 (.024)	-0.014 (.006)	0.049 (.065)
Renter	-0.079 (.009)	0.113 (.027)	-0.024 (.008)	0.063 (.094)
Promotion Opportunities	0.033 (.007)	0.286 (.02)	0.024 (.004)	0.635 (.052)
Has second job	-0.040	-0.058	-0.032	-0.226

Organisation type dummies (7)	(.011)	(.029)	(.007)	(.081)
Yes	Yes	Yes	Yes	Yes
Work time: Mornings only	-0.149	0.110	-0.077	0.005
	(.015)	(.05)	(.012)	(.155)
Work time: Afternoons only	-0.131	0.120	-0.101	-0.301
	(.022)	(.096)	(.021)	(.259)
Work time: Evenings only	-0.092	0.059	-0.084	-0.320
	(.022)	(.07)	(.017)	(.204)
Work time: At night	0.074	-0.126	0.054	-0.422
	(.025)	(.071)	(.017)	(.202)
Work time: Both lunch/eves	-0.074	-0.191	-0.068	-0.776
	(.033)	(.091)	(.026)	(.314)
Work time: Other times/day	-0.145	-0.048	-0.045	-0.007
	(.062)	(.153)	(.033)	(.385)
Work time: Rotating shifts	0.065	-0.093	0.041	-0.156
	(.011)	(.034)	(.009)	(.101)
Work time: Varies/no pattern	-0.009	-0.022	0.045	-0.084
	(.019)	(.051)	(.011)	(.125)
Work time: Daytime and Evening	0.001	0.008	0.006	-0.008
	(.018)	(.041)	(.01)	(.116)
Work time: Other	-0.061	0.022	0.028	0.337
	(.035)	(.1)	(.025)	(.335)
Incentive Payments	0.054	0.030	0.035	0.089
	(.007)	(.02)	(.005)	(.053)
Trade Union Recognised	0.031	-0.004	0.052	0.058
	(.009)	(.027)	(.007)	(.077)
Pension Member	0.109	-0.011	0.067	0.045
	(.009)	(.026)	(.007)	(.079)
Region Dummies (18)	Yes	Yes	Yes	Yes
Industry Dummies (54)	Yes	Yes	Yes	Yes
Occupation Dummies (73)	Yes	Yes	Yes	Yes
Wave 2	0.075	-0.094	---	---
	(.011)	(.037)		
Wave 3	0.093	-0.142	0.095	0.117
	(.007)	(.027)	(.006)	(.068)
Wave 4	0.130	-0.183	0.150	-0.026
	(.007)	(.026)	(.005)	(.064)
Wave 5	0.151	-0.165	0.195	0.007
	(.007)	(.025)	(.006)	(.066)
Wave 6	0.178	-0.149	0.234	0.042
	(.008)	(.026)	(.006)	(.07)
Wave 7	0.204	-0.129	0.288	0.056
	(.009)	(.029)	(.007)	(.079)
Wave 8	0.212	-0.145	0.338	-0.033
	(.016)	(.052)	(.012)	(.141)
Wave 9	0.252	-0.147	0.403	0.013
	(.017)	(.055)	(.013)	(.146)
Constant	2.475	---	4.092	---
	(.077)		(.043)	

Mu(1)	---	-2.838 (.193)	---	---
Mu(2)	---	-2.455 (.193)	---	---
Mu(3)	---	-1.794 (.192)	---	---
Mu(4)	---	-0.521 (.192)	---	---
Number of observations	24746	24746	24646	14842
R-Squared	0.806	---	---	---
Log Likelihood	---	-34365.45	---	-6009.44
Log Likelihood at Zero	---	-36094.98	---	-6334.94

Table 2. Correlations Between Estimated Wage and Job Satisfaction Coefficients.

		<i>Occupation</i>		<i>Industry</i>	
		Robust	Spearman	Robust	Spearman
All (Level)	Estimated Coefficients	1.67	0.18	-0.85	-0.08
	T-statistics	<b>3.01</b>	<b>0.30</b>	-1.00	-0.13
All (Panel)	Estimated Coefficients	1.35	0.20	3.42	0.20
	T-statistics	<b>2.72</b>	<b>0.30</b>	1.39	0.23
Women	Estimated Coefficients	0.71	-0.03	-0.61	-0.03
	T-statistics	1.17	0.10	-0.40	0.03
Men	Estimated Coefficients	<b>2.26</b>	<b>0.28</b>	-0.06	-0.03
	T-statistics	<b>4.95</b>	<b>0.53</b>	-0.04	-0.07
Young	Estimated Coefficients	<i>4.46</i>	<b>0.29</b>	-0.87	-0.07
	T-statistics	<b>4.59</b>	<b>0.41</b>	-1.23	-0.13
Old	Estimated Coefficients	0.34	0.04	0.40	0.03
	T-statistics	0.42	0.03	0.14	0.06
High-Educated	Estimated Coefficients	0.56	0.12	0.58	-0.02
	T-statistics	<b>2.70</b>	<b>0.34</b>	-0.60	-0.09
Not High-Educated	Estimated Coefficients	1.05	0.14	-2.05	-0.06
	T-statistics	1.69	<b>0.25</b>	-0.90	-0.08
Private Firms	Estimated Coefficients	1.06	0.14	-0.36	0.01
	T-statistics	<b>3.23</b>	<b>0.32</b>	0.25	0.06
Public Firms	Estimated Coefficients	0.88	0.10	<i>-1.85</i>	-0.38
	T-statistics	1.00	0.08	-1.04	-0.29

Note: All statistics are bootstrapped with 1000 replications. **Bold** = significant at the five per cent level; *Italic* = significant at the ten per cent level.

Table 3. Getting to the Good Jobs: Occupations

Job Quality by Previous Labour Force Status

<i>Previous LF status</i>	<b>Job Quality</b>		N
	Not High	High	
Employed/self-employed	65.2	34.8	9599
Unemployed	77.4	22.6	3564
Looking after family	70.6	29.4	1304
F-T education	78.0	22.0	1137
Something else	69.8	30.2	1037
<b>Total</b>	<b>69.4</b>	<b>30.6</b>	<b>16641</b>

$\chi^2(4) = 227.9$

Job Quality by Reason for Leaving Last Job

<i>Reason last job ended</i>	<b>Job Quality</b>			<u><math>\Delta</math> occupational wage coeff*100</u>	<u><math>\Delta</math> occupational job satisfaction coeff*100</u>
	Not High	High	N		
Promoted	55.4	44.6	2412	3.26	1.54
Left for better job	67.6	32.4	3238	2.08	0.76
Made redundant	74.4	25.6	644	-1.74	0.38
Dismissed or sacked	84.3	15.7	108	-0.91	-1.23
Temporary job ended	70.6	29.4	795	0.52	-0.37
Other reason	67.1	32.9	2061	-1.16	0.08
<b>Total</b>	<b>65.3</b>	<b>34.7</b>	<b>9258</b>	<b>1.32</b>	<b>0.72</b>

$\chi^2(5) = 164.6$

Job Quality by Previous Job Quality

**NON-PROMOTEES**

<i>Previous job quality</i>	<b>Job Quality</b>		
	Not High	High	N
Not High	84.0	16.0	1906
High	33.9	66.1	923
<b>Total</b>	<b>67.7</b>	<b>32.3</b>	<b>2829</b>

**PROMOTEES**

<i>Previous job quality</i>	<b>Job Quality</b>		
	Not High	High	N
Not High	77.9	22.1	688
High	15.2	84.8	454
<b>Total</b>	<b>53.0</b>	<b>47.0</b>	<b>1142</b>



Table 4. Occupational Wage Rents and Social Status: Correlations

*Bivariate correlations with social status*

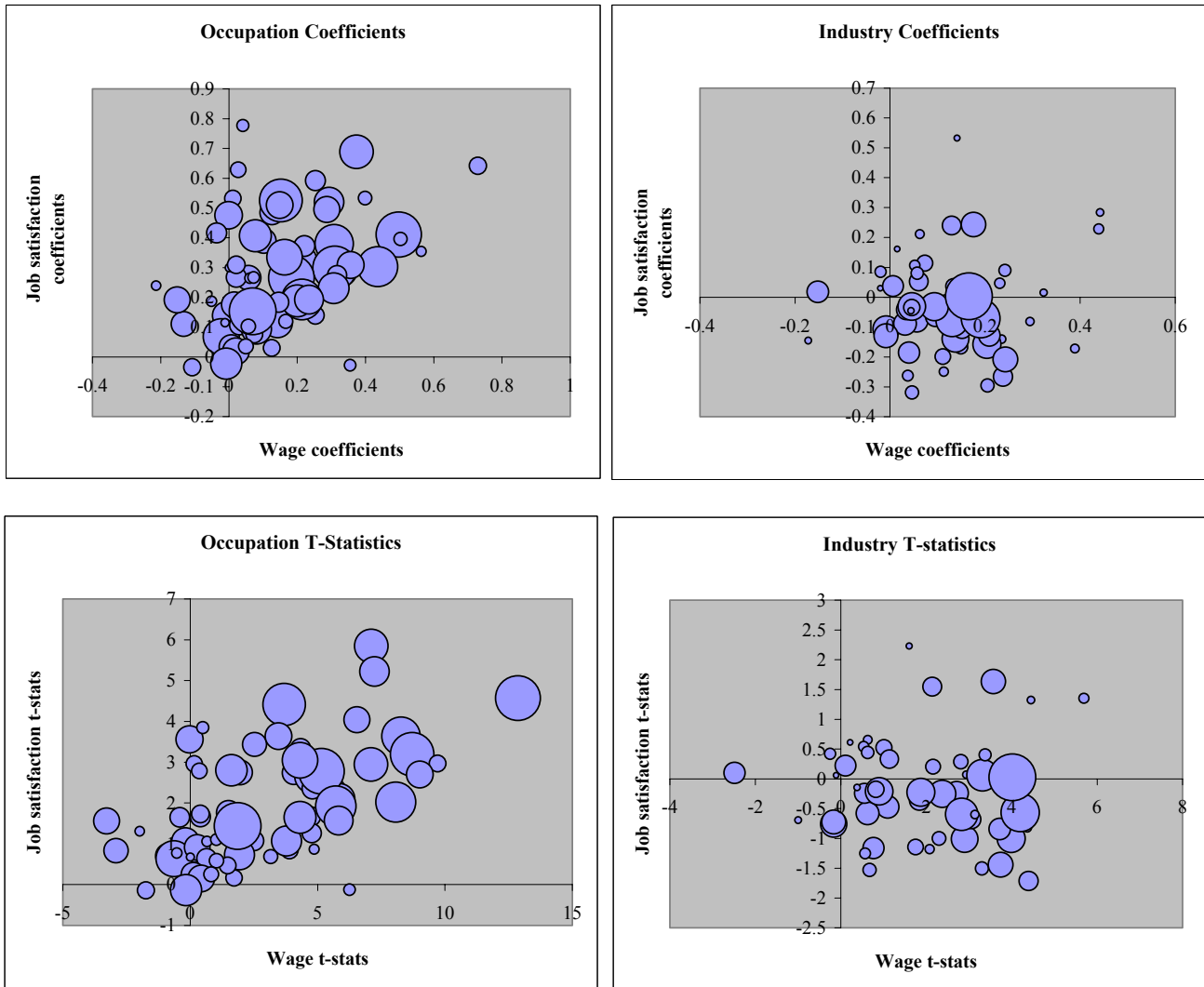
	<u>Spearman rank correlation coefficient</u>	<u>t-statistic</u>
Occupational part of wages	<b>0.679</b> (0.1%)	<b>3.42</b>
Non-occupational part of wages	0.429 (5.3%)	1.65
Residual part of wages	0.276 (28%)	1.33

*Multivariate regression of social status on wages*

Occupational part of wages	<b>4.591</b> <b>(1.878)</b>
Non-occupational part of wages	0.099 (.934)
Residual part of wages	-3.200 (18.2)
Constant	-0.689 (6.392)
N	21

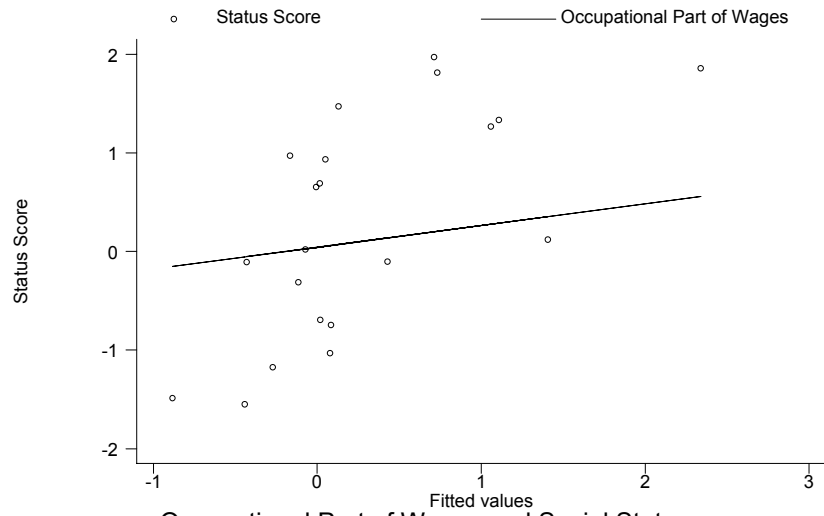
Note: **Bold** = significant at the five per cent level; *Italic* = significant at the ten per cent level.

Figure 1. The Relation between Estimated Coefficients in Wage and Job Satisfaction Regressions (Results for Men)

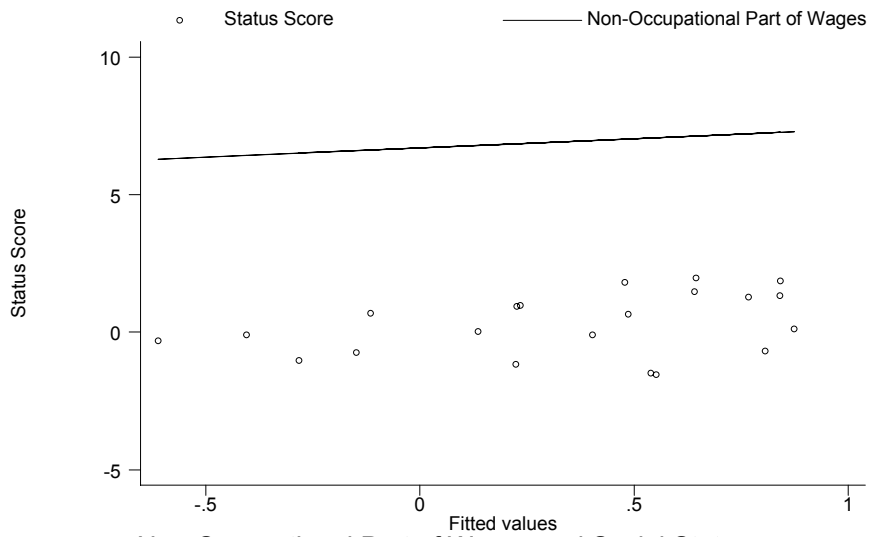


Note: The size of the points represents the number of individuals in the estimation sample in the occupation or industry.

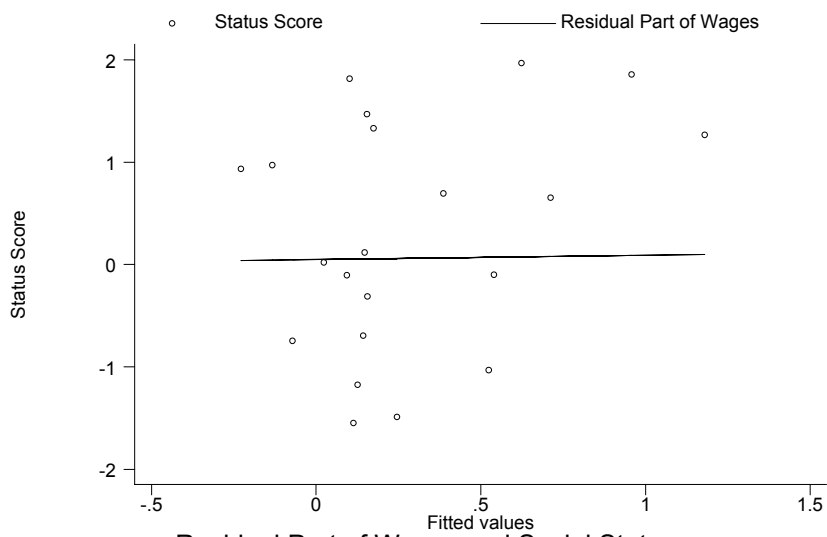
Figure 2. Occupational Wage Rents and Social Status.



Occupational Part of Wages and Social Status



Non-Occupational Part of Wages and Social Status



Residual Part of Wages and Social Status

## Matching and Job Disamenities

Consider two types of workers, A and B. Their utility function is linear:

$$U_i = \alpha w - \beta_i D; \quad i = A, B.$$

Assume that B's are less affected by hard work:  $\beta_A > \beta_B$ . There are two types of job: "easy jobs", subscripted by E, which pay  $w_E$  and involve job disamenities of  $D_E$ ; and "hard jobs", subscripted by H, which pay  $w_H$  and involve job disamenities of  $D_H$ .

A worker of type A will choose an easy job if:

$$\alpha w_E - \beta_A D_E > \alpha w_H - \beta_A D_H \quad \Leftrightarrow \quad w_H < w_E + (\beta_A/\alpha)(D_H - D_E) \quad (1)$$

If  $w_H$  is higher than this, the A's will prefer the hard job. Similarly, a worker of type B will choose a hard job if

$$\alpha w_H - \beta_B D_H > \alpha w_E - \beta_B D_E \quad \Leftrightarrow \quad w_H > w_E + (\beta_B/\alpha)(D_H - D_E) \quad (2)$$

There are thus three possible situations:

- (i)  $w_H > w_E + (\beta_A/\alpha)(D_H - D_E)$ : Both A and B prefer the hard job.
- (ii)  $w_E + (\beta_B/\alpha)(D_H - D_E) < w_H < w_E + (\beta_A/\alpha)(D_H - D_E)$ : There is sorting on the labour market.
- (iii)  $w_H < w_E + (\beta_B/\alpha)(D_H - D_E)$ : Both A and B prefer the easy job.

In cases (i) and (iii) it is obvious that B's have higher utility than A's (same wages and disamenities, but  $\beta_A > \beta_B$ , so that the B's suffer less from the job disamenities). What about utilities in the sorting equilibrium? The utilities are:

$$U_A^{\text{sort}} = \alpha w_E - \beta_A D_E$$

$$U_B^{\text{sort}} = \alpha w_H - \beta_B D_H$$

Hence  $U_B^{\text{sort}} > U_A^{\text{sort}}$  if

$$w_H > w_E + (1/\alpha)(\beta_B D_H - \beta_A D_E). \quad (3)$$

However, the sorting condition in (ii) requires

$$w_H > w_E + (\beta_B/\alpha)(D_H - D_E) \quad (4)$$

And the right-hand side of (4) is larger than the right-hand side of (3), as  $\beta_A > \beta_B$ .

Whenever there is sorting, the B's (in the "hard jobs") have both **higher wages** and **higher utility**. These are not rents, in the sense that the A's still prefer the easy jobs to the hard jobs in the sorting equilibrium.

## REFERENCES

- Blanchflower, D.G. and Oswald, A.J. (1995), *The Wage Curve*, Cambridge (Mass): MIT Press.
- Chan, T.W., & Goldthorpe, J.H. (2003). "Is There A Status Order in Contemporary British Society? Evidence From the Occupational Structure of Friendship". University of Oxford, mimeo.
- Chan, T.W., & Goldthorpe, J.H. (2003). "Social Status and Newspaper Readership". University of Oxford, mimeo.
- Clark, A.E. (1996), "Job Satisfaction in Britain", *British Journal of Industrial Relations*, 34, pp.189-217.
- Clark, A.E. (1997), "Job Satisfaction and Gender: Why are Women so Happy at Work?", *Labour Economics*, 4, pp.341-372.
- Clark, A.E. (1998), "What Makes a Good Job? Evidence from OECD Countries", LEO, University of Orléans, Discussion Paper No.98-26.
- Clark, A.E. (2001), "What Really Matters in a Job? Hedonic Measurement Using Quit Data", *Labour Economics*, 8, pp.223-242.
- Clark, A.E. (2003), "Unemployment as a Social Norm: Psychological Evidence from Panel Data", *Journal of Labor Economics*, 21, pp.323-351.
- Clark, A.E., Georgellis, Y., and Sanfey, P. (1998), "Job Satisfaction, Wage Changes and Quits: Evidence from Germany", *Research in Labor Economics*, 17, pp.95-121.
- Clark, A.E. and Oswald, A.J. (1996), "Satisfaction and Comparison Income", *Journal of Public Economics*, 61, pp.359-381.
- Clark, A.E., A.J. Oswald and Warr, P.B. (1996), "Is Job Satisfaction U-shaped In Age?", *Journal of Occupational and Organizational Psychology*, 69, pp.57-81.
- Clegg, C.W. (1983), "Psychology of Employee Lateness, Absence and Turnover: A Methodological Critique and an Empirical Study", *Journal of Applied Psychology*, 68, pp.88-101.
- Gibbons, R. and Katz, L. (1992), "Does Unmeasured Ability Explain Inter-Industry Wage Differentials?", *Review of Economic Studies*, 59, pp.515-35.
- Godechot, O., & Gurgand, M. (2000). "Quand les salariés jugent leur salaire". *Economie et Statistique*, **331**, 3-24.

- Goux, D. and Maurin, E. (1999), "Persistence of Interindustry Wage Differentials: A Reexamination Using Matched Worker-Firm Panel Data", *Journal of Labor Economics*, 17, pp.492-533.
- Greene, W. (1993), *Econometric Analysis*, 3<sup>rd</sup> Edition, Upper Saddle River, NJ: Prentice-Hall.
- Haisken-DeNew, J. and Schmidt, C. (1998), "Industry Wage Differentials Revisited: A Longitudinal Comparison of Germany and USA", University of Munich, mimeo.
- Hwang, H., Reed, W.R. and Hubbard, C. (1992), "Compensating Wage Differentials and Unobserved Productivity", *Journal of Political Economy*, 100, 835-858.
- Kawaguchi, D. (2003). "Compensating Wage Differentials among Self-Employed Workers: Evidence from Job Satisfaction Scores". University of Tsukuba, mimeo.
- Kolev, A. (1999), "Three Essays on Living Standards and Access to Alternative Sources of Labour Income", PhD Thesis, European University Institute.
- Lalive, R. (2002), "Do Wages Compensate for Workplace Amenities?", University of Zurich, mimeo.
- Mangione, T.W. and Quinn, R.P. (1975), "Job Satisfaction, Counterproductive Behavior, and Drug Use at Work", *Journal of Applied Psychology*, 60, pp.114-16.
- Patterson, M., West, M., Lawthorn, R. and Nickell, S. (1997), "Impact of People Management Strategies on Business Performance", Institute of Personnel and Development, Issues in People Management No.22.
- Rose, M. (2003). "Good deal, bad deal? Job satisfaction in occupations". *Work, employment and society*, 17, 505-532.