

Do Different Work Characteristics Have Different Distributional Impacts on Job Satisfaction? A Study of Slope Heterogeneity in Workers' Well-Being

Aekapol Chongvilaivan*

Institute of Southeast Asian Studies

Nattavudh Powdthavee**

London School of Economics and University of Melbourne

20th March 2012

Forthcoming in the *British Journal of Industrial Relations*

* Institute of Southeast Asian Studies (ISEAS), 30 Heng Mui Keng Terrace, Singapore 119614, Tel: +65-6870-4530; Fax: +65-6778-1735; Email address: aekapol@iseas.edu.sg.

** London School of Economics, Houghton, Houghton Street, London, WC2A 2AE, UK. Tel: +44-7990-815924; Email address: n.powdthavee@gmail.com.

Abstract

This paper is an empirical study of slope heterogeneity in job satisfaction. It provides evidence from the generalized ordered probit models that different job characteristics tend to have different distributional impacts on the overall job satisfaction. For instance, standard models tend to significantly underestimate the effects of monthly salary and hours worked at generating the “highly” satisfied workers, whilst lowering the incidence of the “very dissatisfied” workers. Although our results should be viewed as illustrative, we provide discussions of their potential implications for employers and on how they could help with the design of employment contracts.

JEL: J53, D61

Keywords: job satisfaction; heterogeneity; employment contract; generalized ordered probit; salary; work-life balance

1. Introduction

Most empirical work on the determinants of job satisfaction uses either linear regression or single-index ordered probit and logit models. While the latter account for discreteness and ordering of job satisfaction, they impose an implicit cardinalization such that the trade-off ratios between, say, income and work hours must be constant across the distribution of job satisfaction (see, e.g., [Boes and Winkelmann, 2006](#)). For example, if an increase in salary of 2% is required on average to offset a fall in overall job satisfaction from an increase in the number of work hours by 1%, then this trade-off ratio is assumed to remain *constant* across different parts of the job-satisfaction distribution. In other words, the standard ordered probit and logit models do not allow for the potential heterogeneous effects that income and work hours could have on the little-satisfied group as opposed to the highly satisfied group, thus discounting any possibilities of shortcuts to achieving the highest incidence of highly satisfied workers without having to make large sacrifices in other areas in return.

Recent econometric evidence, however, suggests that the implicit cardinalization of subjective well-being data may be too strong. For instance, [Boes and Winkelmann \(2010\)](#) have shown that income significantly reduces the incidence of people reporting low satisfaction with life overall but does not increase the incidence of high life satisfaction among men in Germany. Mentzakis (2011) also reports a considerable heterogeneity in the compensation variation for different types of health problems across different parts of the life-satisfaction distribution. Despite finding statistically insignificant average effect of grandparenthood on life satisfaction, Powdthavee (2011) shows that being a grandparent increases the probability of individuals reporting to be “very satisfied” with life overall. In short, there is increasing empirical evidence from studies that use less restrictive models that heterogeneity in subjective data matters in terms of what inferences we can draw from the estimation results.

Our paper follows the recent literature and explores what happens if the effects of many of the studied job characteristics such as incomes, work hours, and promotion opportunities are in fact different in different parts of the job-satisfaction distribution. What lessons can we learn from this, and what implications might this have on the employer–employee relations literature? To the best of our knowledge, empirical evidence on the heterogeneous effect of job characteristics on different parts of the job-satisfaction distribution is scarce, and discussions on the implications of such evidence are virtually non-existent. For this reason, our paper aims to fill this gap in the literature.

The remainder of this paper can be structured as follows. Section 2 reports our data set and presents descriptive statistics of our main variables. Section 3 develops our empirical strategy based on the generalized probit model and attempts to account for potential selection biases. Empirical results are discussed in Section 4. Section 5 concludes this paper with some implications.

2. Data

The data set comes from Waves 2–18 of the British Household Panel Survey (BHPS).¹ This is a multi-purpose study and a nationally representative sample of British households, containing over 15,000 adult individuals across UK. The survey has been conducted between September and Christmas of each year from 1991 to 2010, and is available for download from the UK Data Archive (www.data-archive.ac.uk).

From Wave 1 onward, individuals are asked to rate in confidence their levels of satisfaction with their jobs overall. Responses are given on a seven-point scale, ranging from 1 “very dissatisfied” to 7 “very satisfied”. We focus our attention on individuals of working

¹ Because of the change in the labelling of response categories between Wave 1 and all subsequent waves of the BHPS ([Conti & Pudney, 2011](#)), we have decided to exclude Wave 1 from our analysis.

age (16–65) in paid employment and working in the private sector,² as well as the self-employed, who also reported a level of job satisfaction in any given wave. This produces a nationally representative sample of 72,724 observations (14,917 individuals). Of those, 33,249 observations (7,376 individuals) are women, 39,475 observations (7,541 individuals) are men. Approximately 63% of the full sample are age 40 or under. The average real salary is approximately £913 per month, and the average number of hours worked is 34 per week. Most individuals are in a permanent job (97%); around 34% are in a job with promotion opportunities; 17% are union members; and almost 25% have to make a (one way) journey of more than 30 minutes to work every day. Descriptive statistics of the main variables used in this paper’s analysis can also be found in Table 1A in the Appendix.

Most people seem to be “highly” (to “very”) satisfied with their job; approximately 45% of the British private and self-employed workers report a “6” on the seven-point job-satisfaction scale, while 13% report to be “very satisfied” with their jobs overall (see the distribution of self-reported overall job satisfaction in Figure 1).

3. Empirical strategy

The standard ordered probit model typically used in the estimation of job satisfaction can be formally written as follows:

$$\Pr(JS_{it} = j | X_{it}) = \Phi(\omega_j - X_{it}\theta) - \Phi(\omega_{j-1} - X_{it}\theta) \quad j = 1, \dots, J \quad (1)$$

where $i = 1, \dots, n$. The dependent variable $JS_i \in \{1, \dots, J\}$ represents a self-reported level in response to an overall job-satisfaction question for individual $i = 1, \dots, n$ at time $t = 1, \dots, T$; ω_j denotes the threshold values, where $\omega_0, \dots, \omega_J$; θ is a vector of parameter estimates; and

² It is possible that the determinants of job satisfaction significantly differ between public and private sector workers. However, in order to keep our sample of workers to be as a priori homogenous as possible, we have decided to focus our attention in the current study only on those workers in the private sector.

$\Phi(\bullet)$ denotes the cumulative density function (CDF) in which the variance, without loss of generality, is normalized to unity. The vector of explanatory variables, X , includes log of pay per month (in real terms), job tenure, job tenure squared, log of work hours per week, firm size, a dummy representing whether the job is permanent or temporary, dummies for commuting time to work, union membership, opportunity for employment to work, and a dummy representing whether there is a pension scheme at the workplace, as well as the respondent's non-work variables, which are age, age squared, gender, health status, marital status, education, race dummies, occupational sector dummies, regional dummies, and wave dummies. Since it holds that $\omega_0 = -\infty$ and $\omega_J = \infty$, then $\Phi(\omega_0 - X_{it}\theta) = 0$; and $\Phi(\omega_J - X_{it}\theta) = 1$. As usual, the maximum-likelihood procedure is employed to estimate the vector of parameter estimates, θ , along with ω_j in the job-satisfaction equation (1).

However, this conventional approach implicitly imposes a rather strong assumption that the job-satisfaction trade-off is homogenous across the distribution of outcomes, and, if the trade-off heterogeneity exists, may lead to biased and inconsistent estimates ([Mentzakis, 2011](#); [Boes and Winkelmann, 2010](#)). Since our key interest zeroes in on sensitivity with respect to the levels of job satisfaction, we opt for a more flexible framework of the generalized ordered probit estimation, where the effects of income and other characteristics across different levels of job satisfaction are unrestricted. The generalized setting can be written as:

$$JS_{it}^* = X_{it}\theta_j + u_{it}; \quad (2)$$

$$JS_{it} = j \text{ if } \omega_{j-1} < JS_{it}^* \leq \omega_j \text{ for } j = 1, \dots, J, \quad (3)$$

where JS_{it}^* is the (unobserved) latent variable of job satisfaction associated with the (observed) response outcomes, JS_{it} ; and $\omega_{ij} = \omega_j + X_{it}\lambda_j$. Heterogeneity enters the generalized ordered model in (2) and (3) in such a way that the threshold values, ω_{ij} , are

allowed to be a linear function of regressors, X_{it} , making the vector of parameter estimates, θ_j , and thus the marginal effects on satisfaction category-specific. The generalized ordered probit model can be depicted as:

$$\Pr(JS_{it} = j|X_{it}) = \Phi(\omega_j - X_{it}\theta_j) - \Phi(\omega_{j-1} - X_{it}\theta_{j-1}), \quad (4)$$

where $\theta_j = \theta - \lambda_j$. In addition, a well-defined likelihood requires that the order restriction is satisfied. That is, $\omega_j - X_{it}\theta_j \leq \omega_{j+1} - X_{it}\theta_{j+1}$, for all i and j .

In the generalized ordered probit, the marginal probability effects of independent variables on job satisfaction are heterogeneous across different levels of satisfaction. In other words, the standard ordered probit model is nested in the generalized model (4) through the constraint $\theta_1 = \dots = \theta_J$ (Boes and Winkelmann, 2004). Therefore, additional flexibility provided by relaxation of this restriction in the generalized model illuminates clearer insights into the satisfaction trade-off as the marginal probability effects run from the lowest to the highest job satisfaction.³ In panel data, equation (4) can be generalized further to allow for individual-specific random effects, μ_i ,

$$\Pr(JS_{it} = j|X_{it}, \mu_i) = \Phi(\omega_j - X_{it}\theta_j - \mu_i) - \Phi(\omega_{j-1} - X_{it}\theta_{j-1} - \mu_i), \quad (5)$$

where $COV(\mu_i, X_{it})$ is assumed to be 0. In cases where the assumption of no correlation between μ_i and X_{it} is violated, it is possible to follow the idea of Chamberlain (1980) under a Mundlak (1978) restriction to allow for possible correlation between μ_i and X_{it} as follows:

$$\mu_i = \bar{X}_i + \alpha_i, \quad (6)$$

where \bar{X}_i is the average of X_{it} over time (see also: Boes and Winkelmann, 2010; Mentzakis, 2011).

³ As Boes and Winkelmann (2004) highlight, the additional flexibility that the generalized ordered probit model offers does not come without costs. Now that the order restrictions have to be satisfied, computation of the generalized ordered probit estimates tends to be considerably tedious.

4. Estimation results

4.1. Pooled cross section

The standard ordered probit (OPROBIT) estimates and generalized ordered probit (GOPROBIT) estimates are presented in Table 1.⁴ The set of controls is as stated in equation (1). In the generalized model, six parameter vectors are estimated (where each vector contains coefficients for all the explanatory variables). All equations are estimated using STATA11.1 with robust standard errors and clustering by personal identification.

While we cannot interpret the estimated coefficients from either model directly, as the marginal effects of job characteristics on overall job satisfaction will be derived later, the comparisons of parameter estimates are useful for understanding our results. For example, if we were to focus our attention on the log of real-pay-per-month coefficients, we can see that they are twice or nearly twice as large for the parameters θ_1 to θ_4 , and slightly larger for θ_5 , than the overall estimate in the standard model. The estimate is close to a zero point estimate and is statistically insignificant at all conventional levels for the parameter θ_6 . A similar pattern of decreasing point estimates as we move up the parameters from θ_1 to θ_6 is also observed for the estimated coefficients on log of hours worked per week and promotion opportunity. However, this does not apply to all variables; for instance, with respect to the firm size of 500+ employees, most of the parameters are only slightly different from the point estimate obtained in the standard model. A Wald test on the generalized ordered probit model against the standard model also suggests that we can reject the null hypothesis of equal slope

⁴ There may be some selection bias into employment for those who are more satisfied at work. We perturb our base-line estimations by using Heckman's (1979) selection model where employment is endogenously determined by various socio-economic variables, and find that our main findings are qualitatively unchanged. We however are in favour of the results based on the employee samples as our interest rests with the relationship between job satisfaction and characteristics of those who work only. The results of the selection model are available upon request.

parameters ($\chi^2_{434} = 4608.08$).⁵ In addition, the null hypothesis of equal coefficients can be rejected for 11 out of 16 job-characteristics variables (we can accept the null of equal slopes for the following variables: workplace pension; commute: 16–30 minutes; commute: 31–60 minutes; commute: 61–90 minutes; and self-employed). Hence, the results provide some of the preliminary evidence that job-characteristics parameters are heterogeneous with respect to the job-satisfaction distribution; in other words, there is *slope heterogeneity* in the job-satisfaction estimates.

4.2. Random effects and Mundlak transformations models

While cross-section models can provide us with suggestive results, they are considered less efficient compared to models that take into account the panel structure of the data set (and in some cases, cross-section models can be inconsistent if there is significant unobserved individual heterogeneity in self-reported job satisfaction). Since the BHPS is a longitudinal data set, it is possible to allow for the individual-specific random effects to be parameterized in the estimation of job satisfaction. Following [Boes and Winkelmann \(2010\)](#), Table 2 presents estimates taken from the random-effects generalized ordered probit model (RE-GOPROBIT), which allows for the individual differences in job satisfaction to be estimated alongside other parameters in the model.

We also provide in Table 3 estimates taken from the random-effects generalized ordered probit model with Mundlak transformations (RE-GOPROBIT-Mundlak). While the RE-GOPROBIT model accounts for individual-specific random effects in panel data sets, its implicit assumption of no individual fixed effects, i.e., zero correlation between unobserved

⁵ The χ^2 statistic is obtained from testing the equality between each of the estimated coefficients in the GOPROBIT model. For example, in the case of log of real pay per month, we test the equality of each pair of coefficients, i.e., $\theta_{1,\lg pay} = \theta_{2,\lg pay}; \theta_{1,\lg pay} = \theta_{3,\lg pay}; \dots; \theta_{1,\lg pay} = \theta_{7,\lg pay}; \theta_{2,\lg pay} = \theta_{3,\lg pay};$ and so on, etc.

individual heterogeneity and the explanatory variables, is often rejected by the data. One could imagine, for example, that people who are born with persistent personality traits that make them happy with work may be more productive in the labour market and earn higher than usual incomes in the process. The effect of these unobserved characteristics may also vary across different parts of the job-satisfaction responses. To account for the possibility of the omitted time-invariant variables bias, a set of within-person averages – or the long-run effects – of the explanatory variables can be included as additional controls in the job-satisfaction equation, that is, simply \bar{X}_i of X_{it} . According to Ferrer-i-Carbonell (2005), this so-called Mundlak transformations model yields similar results on the estimated coefficients of interest to other approaches that factor out individual fixed effects from the estimation.⁶

Comparing the RE-GOPROBIT estimates in Table 2, the RE-GOPROBIT-Mundlak estimates in Table 3, and the GOPROBIT estimates in Table 1, we can see that, for many of the job-characteristics variables, there are little differences – in terms of size and statistical significance – in the point estimates across the three models. For example, the coefficients on the log of real pay per month for parameter θ_1 are 0.212, 0.263, and 0.254 for GOPROBIT, RE-GOPROBIT, and RE-GOPROBIT-Mundlak, respectively. Nevertheless, some of the differences can be seen for parameter θ_6 ; e.g., the RE-GOPROBIT-Mundlak coefficient on the log of real pay per month for parameter θ_6 is 0.073, which is close to the 0.096 obtained by the standard ordered probit model. By contrast, the equivalent coefficients for GOPROBIT and RE-GOPROBIT for parameter θ_6 are noticeably smaller at -0.006 and 0.014, respectively.

4.3. Marginal probability effects and trade-off ratios

⁶ For more examples of the Mundlak applications in subjective well-being data, see Mentzakis (2011) and Powdthavee and Van Den Berg (2011).

It is tempting to conclude based on the above results that whether or not the unobserved individual heterogeneity in the data set is accounted for makes only small differences to the point estimates but may result in large differences when one ignores the slope heterogeneity in job characteristics in job-satisfaction equations.⁷ However, we must first be able to interpret the estimated parameters directly and engage in formal comparisons of outcomes across models. According to [Boes and Winkelmann \(2010\)](#), there are two ways to interpret the standard and generalized ordered probit models. The first is the marginal probability effects (MPE) of each job attribute evaluated at the sample means on job satisfaction, and the second involves the trade-off ratios between job characteristics. The former shows how one attribute affects the job-satisfaction distribution for an average person, while the latter method demonstrates how much one aspect of the job has to change in order to compensate for having to go without the other, e.g., how much additional income in % is required to compensate an average worker for a 1% increase in the number of hours worked per week. This differs from the first method as the second implicitly responds to the heterogeneous effects of both job attributes simultaneously.

All of the MPEs are calculated from regression analysis in Tables 1–3. This produces fairly dense tables of statistical results. For ease of presentation, we choose to present only the estimated MPEs of the following job characteristics in Figures 2A–C: log of pay per month; log of hours worked per week; promotion opportunity.

Looking across the figures, we can see that there is considerable heterogeneity in the MPEs across job characteristics. For example, in Figure 2A, the MPE of log of pay per month on the probability of reporting a job-satisfaction score of “6” is approximately $(0.02 \times 100 =)$ 2% when it is estimated using the OPROBIT. By contrast, the equivalent MPE is around 6%

⁷ This is important because, if there really are little differences in the point estimates between GOPROBIT, RE-GOPROBIT, and RE-GOPROBIT-Mundlak, then researchers can simply estimate GOPROBIT on cross-section data without having to worry about potential unobserved heterogeneity bias contaminating their results.

when we allow for heterogeneity in overall job satisfaction (e.g., see the MPEs obtained from the remaining three generalized ordered probit models). With respect to the “very satisfied” group, the OPROBIT’s MPE is, again, approximately 2%. On the other hand, the MPEs from both GOPROBIT and RE-GOPROBIT are estimated to be closer to zero and are not statistically significant at conventional levels. Controlling for individual fixed effects, however, raises the MPE back to around 1.7%, which is statistically indistinguishable from the MPE produced by OPROBIT. This implies that a 1% increase in pay per month increases the probability of individuals reporting to be either “6” or “7” on the job-satisfaction scale by 4% in the more restrictive model compared to around 6–8% in the less restrictive models. However, since the sum of all MPEs should equal 0, we also see that a 1% increase in pay per month significantly reduces the probability of individuals reporting to be “neither satisfied or dissatisfied” with work (or “4”) and the low-satisfaction (those reporting to be “1”, “2”, or “3”) group.

There is almost a reversal in the pattern of MPE in the hours worked per week; as illustrated in Figure 2B, a 1% increase in the number of hours worked per week is associated with a reduction in the probability of an average person reporting to be “6” on the job-satisfaction scale by approximately 6% in the OPROBIT model, and almost 10% in the generalized ordered probit models. However, pooling the “6” and “7” job-satisfaction scales together we find that a 1% increase in the number of hours worked is associated with a reduction in the probability of an average individual reporting to be in these two categories by approximately 12%-13%, which is the almost same across all four models.

With respect to the MPE of promotion opportunities (Figure 2C), a move from 0 to 1 increases the probability of individuals reporting to be “very satisfied” with their jobs by approximately 6% in the OPROBIT model and slightly less than 4% in all three generalized models. The difference of around 2%, which is statistically significant at conventional levels,

implies that there is a possible overestimation of the impact of promotion opportunities on overall job satisfaction when the standard ordered probit is used to estimate the job-satisfaction equation.

It should be highlighted that MPEs can also be presented in their normalized form – the estimated MPEs obtained in Figures 2A-2C divided by the baseline job-satisfaction distribution reported in Figure 1. For instance, a 1% increase in the monthly income raises the probability of individuals reporting to be “very satisfied” by approximately 2% in the standard model. Considering that around 13% of people fall within this group, the normalized MPE for monthly income for the “very satisfied” group is therefore 15% ($= (2/13) \times 100$). In other words, a 1% increase in the monthly income results in an increase in the proportion of people reporting to be “very satisfied” with their jobs from 13% to 15%, which is equivalent to a 15% increase from the baseline level, holding other things constant.

The relationship between the MPEs of different job attributes at various parts of the overall job-satisfaction distribution can also be illustrated by trade-off ratios. For illustrative purposes, we present the following three scenarios of trade-off ratios in Figures 3A–C:

- 1) log of hours worked per week/log of pay per month,
- 2) promotion opportunities/log of hours worked per week, and
- 3) promotion opportunities/log of hours worked per week.

We normalize all MPEs to have positive values so that the trade-off ratios range from 0 to ∞ .⁸ With this transformation, Figure 3A is equivalent to showing how much additional pay per month is required to compensate for a 1% increase in the number of hours worked per week; Figure 3B illustrates how much additional pay per month is equivalent to having promotion opportunities at the workplace; and Figure 3C shows how much hours worked per

⁸ Excluding the negative income coefficient estimated in the GOPROBIT model on the “very satisfied” category.

week must be reduced to compensate for having no promotion opportunities at the workplace, holding the job-satisfaction distribution fixed.

In order to offset a 1% increase in the number of hours worked per week, pay per month must go up by approximately 3% in the OPROBIT model. By construction, the 3% trade-off ratio is the same for all levels of job satisfaction when the equation is estimated using the standard model. In the generalized models, the income change varies from 1.7% to 8.5% in the GOPROBIT; from 1.5% to 16.9% in the RE-GOPROBIT; and from 1.4% to 3.5% in the RE-GOPROBIT-Mundlak. The latter result is particularly interesting as it implies almost zero differences in the estimated trade-offs between the standard model and the generalized model with Mundlak transformations. In other words, the ratio between the effects of income and hours worked is likely to be constant across the distribution of job satisfaction in equations where individual fixed effects are controlled for. One explanation for this is that, while income in the generalized model compared to the standard model affects much more those who reported “6” on the job-satisfaction scale, hours worked has the same greater effect for the same score on the same models.

We could also use the above principle to calculate the monetary value of promotion opportunities in the workplace. According to Figure 3B, the standard model suggests that an additional pay of around 2.7% is equivalent to a move from 0 to 1 in the “promotion opportunities” dummy for all levels of job-satisfaction distribution. In the generalized models, the monetary values range from 1.2% to 5.3% in the GOPROBIT; from 1.1% to 18.1% in the RE-GOPROBIT; and from 1% to 3.2% in the RE-GOPROBIT-Mundlak. The latter, again, is not so dissimilar to the estimated trade-off obtained in the standard model.

Figure 3C presents the calculated estimates of how much hours worked must be reduced – instead of a rise in pay – in order to “just” offset an average employee from working with no promotion opportunities. The trade-offs here are much more stable than the

trade-offs made between promotion opportunities and income. We can see that, with the standard model, hours worked must be reduced by approximately 0.9% in order to compensate for having no promotion opportunities at the workplace. The equivalent figure ranges from 0.6% to 1% in the GOPROBIT; from 0.6% to 1% in the RE-GOPROBIT; and from 0.4% to 1% in the RE-GOPROBIT-Mundlak.

Finally, we also conduct as part of our analysis a test on the potential differences in the generalized ordered probit estimates by gender and by age group ($40 \leq \text{age} < 40$). Though not reported here, our estimates suggest that there is significant slope heterogeneity in self-rated job satisfaction between male and female workers, as well as between the young and the old. For example, if we were to focus our attention on the log of real-pay-per-month coefficients, we find the estimated parameter θ_6 to be positive and statistically significant only for male workers and not female workers. By contrast, a job that comes with promotion opportunities is associated positively and statistically significantly with a higher probability of the worker reporting to be “very satisfied” with job only for female and not male workers. In addition to this, there is a significantly higher probability of young workers reporting to be “very satisfied” with job compared to the older workers if he or she is on a permanent contract at the workplace. In short, there is also a scope for studies to investigate the slope heterogeneity in workers’ well-being by different socio-demographic statuses.

5. Conclusions

This paper follows Boes and Winkelmann (2010) and uses data from the BHPS (Waves 2–18) to study the potential implications of slope heterogeneity in the job-satisfaction distribution on employer–employee relations. By allowing the correlations between job characteristics and job satisfaction to vary flexibly across the job-satisfaction scale, we are able to show that moderate-to-considerable slope heterogeneity exists among the studied job

attributes – namely monthly salary, hours worked per week, promotion opportunities, time spent commuting to work, union membership, and jobs that include a pension scheme. For instance, log of monthly salary has a higher (absolute) marginal effect on raising the probability of people reporting to be “highly satisfied” (i.e., reporting “6” or “7” on the job-satisfaction scale) in the generalized model (6–8%) than in the standard model (4%); while a 1% decrease in the hours worked per week is associated with a 12%-13% reduction in the probability of people reporting to be “highly satisfied”, which is the approximately same across the generalized and the standard models.

What lessons can we learn from allowing slope heterogeneity of job satisfaction? Our empirical framework which demonstrates the heterogeneous effects of income and non-income characteristics in different parts of job satisfaction distribution, offers at least three main implications. First and foremost, while a wealth of past studies have been devoted to investigating whether employment conditions, both income and non-income, can be translated into job satisfaction, little has been done in the literature to explore for whom these job characteristics can potentially result in the highest well-being at work. [Clark et al. \(2005; p.C119\)](#), for instance, highlight the significance of slope heterogeneity in general by showing that some classes and subgroups of the population “differ in their ability to transform income (and non-income factors) into well being”. Therefore, an attempt in addressing slope heterogeneity in the statistical analysis of job satisfaction yields a clearer insight into how employment conditions shape well-being at work.

Secondly, our empirical exercise that underlines the existence of heterogeneous trade-offs sheds light on the methodology for the future studies on job satisfaction. From a theoretical perspective, modelling an individual’s utility associated with a satisfaction variable necessitates individual heterogeneity and needs to take in the idea that the marginal utility of a satisfaction variable differs across the different levels of well-being. Likewise,

from an empirical perspective, our evidence cautions that the use of the standard ordered probit estimation may generally lead to conclusions that are biased, and the use of more flexible econometric estimations may be preferred. However, it is worth noting that researchers should be aware of the involved trade-offs between choosing efficiency over computation time when choosing the generalized models over the standard models.

Finally, our findings provide an additional incentive to revise the way employment contracts should be designed. Considering that trade-offs with respect to job satisfaction may by and large be heterogeneous, we believe that a more flexible model can help improve upon the conventional approach that uses the estimates of the impacts of employment conditions on workers' well-being as a *guide* in drawing out a standard employment contract.⁹

Like all studies in social sciences, this paper is not without limitations. For example, the dataset used in our analysis is not linked to employer-employee data and, as a result, does not include information on some working variables that are potentially critical determinants of job satisfaction. Since workers are not randomly assigned to firms, it may be possible that the observed slope heterogeneity in the satisfaction distribution for monthly pay is attributable to compensation for the presence of job disamenities. This remains an issue even when we are able to control for industry and social class dummies. Another issue, and generally a pertinent one in social sciences, is that many of our independent variables in the job satisfaction equations are endogenous. These are difficult albeit very important issues. However, because of the limited scope and data availability of this paper, future research will have to come back and address the causality problems much more critically in the context where slope heterogeneity is accounted for in the modelling process.

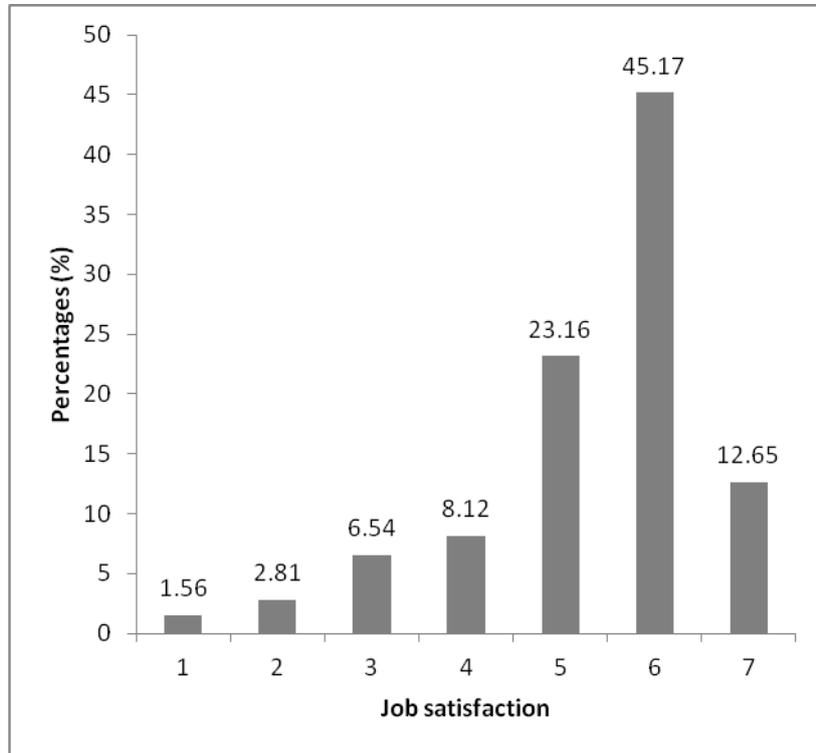
⁹ Nevertheless, it should be noted that the inferred weights that we obtained from our generalized models may not always match that of workers' stated preferences on what, according to them, really matter in their jobs.

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Figure 1: The distribution of overall job satisfaction among workers in the private sector and the self-employed, BHPS September 1992-May 2009



Note: N = 76,053. The responses to the overall job satisfaction question range from 1 “very dissatisfied” to 7 “very satisfied”.

Table 1: Standard ordered probit and generalized ordered probit job satisfaction equations

Dependent variable: Overall job satisfaction	OPROBIT	GOPROBIT					
		θ_1	θ_2	θ_3	θ_4	θ_5	θ_6
Log of pay per month	0.0956** [0.0146]	0.212** [0.0365]	0.197** [0.0259]	0.168** [0.0203]	0.190** [0.0188]	0.135** [0.0175]	-0.00609 [0.0215]
Job tenure	-0.00440 [0.00503]	0.0193 [0.0144]	-0.00904 [0.0101]	-0.0170* [0.00783]	-0.0118+ [0.00672]	-0.00229 [0.00587]	0.000246 [0.00726]
Job tenure^2	-0.000555 [0.000345]	-0.000684 [0.000988]	0.000777 [0.000694]	0.000687 [0.000535]	0.000293 [0.000463]	-0.000732+ [0.000403]	-0.00143** [0.000503]
Firm size: 10-49	-0.151** [0.0168]	-0.0381 [0.0404]	-0.0320 [0.0287]	-0.0673** [0.0233]	-0.101** [0.0212]	-0.159** [0.0195]	-0.183** [0.0225]
Firm size 2: 50-499	-0.289** [0.0180]	-0.158** [0.0414]	-0.176** [0.0295]	-0.199** [0.0240]	-0.233** [0.0227]	-0.299** [0.0213]	-0.335** [0.0251]
Firm size 3: 500+	-0.275** [0.0233]	-0.188** [0.0544]	-0.237** [0.0402]	-0.198** [0.0326]	-0.236** [0.0300]	-0.287** [0.0280]	-0.301** [0.0343]
Pension scheme	-0.230** [0.0408]	-0.00397 [0.0992]	-0.102 [0.0692]	-0.120* [0.0565]	-0.239** [0.0488]	-0.280** [0.0446]	-0.187** [0.0536]
Union member	-0.0509** [0.0142]	0.00474 [0.0352]	-0.0427+ [0.0246]	-0.0603** [0.0196]	-0.0489** [0.0182]	-0.0493** [0.0167]	-0.0627** [0.0210]
Promotion	-0.0815** [0.0221]	-0.0444 [0.0573]	-0.0799+ [0.0410]	-0.138** [0.0325]	-0.136** [0.0295]	-0.101** [0.0276]	-0.0122 [0.0357]
Permanent job	0.0398* [0.0162]	0.354** [0.0314]	0.359** [0.0217]	0.342** [0.0172]	0.335** [0.0156]	0.265** [0.0145]	0.188** [0.0191]
Commute: 16-30 mins	0.267** [0.0121]	0.0585 [0.0521]	0.142** [0.0363]	0.159** [0.0285]	0.179** [0.0258]	0.207** [0.0235]	0.151** [0.0302]
Commute:31-60 mins	0.194** [0.0205]	-0.0313 [0.0324]	-0.0528* [0.0230]	-0.0563** [0.0185]	-0.0619** [0.0170]	-0.0654** [0.0160]	-0.0627** [0.0199]
Commute: 61-90 mins	-0.0618** [0.0134]	-0.0275 [0.0421]	-0.0539+ [0.0295]	-0.0845** [0.0236]	-0.0880** [0.0225]	-0.0933** [0.0210]	-0.0948** [0.0269]
Commute: 91+ mins	-0.0860** [0.0171]	-0.146+ [0.0859]	-0.162* [0.0649]	-0.236** [0.0540]	-0.215** [0.0483]	-0.226** [0.0456]	-0.205** [0.0606]
log of hours work pw	-0.200** [0.0365]	0.139 [0.172]	-0.0936 [0.0910]	-0.170* [0.0724]	-0.204** [0.0657]	-0.0755 [0.0629]	0.0982 [0.0910]
Self-employed	-0.0541 [0.0572]	-0.380** [0.0531]	-0.408** [0.0370]	-0.387** [0.0282]	-0.380** [0.0251]	-0.323** [0.0227]	-0.176** [0.0272]
Log likelihood	-106474.4			-105057.2			
Observations	72724			72724			

Note: +<10%; *<5%; **<1%. N=76,053. Standard errors are in parentheses. Reference groups are: job size: 1-9 people and commute: 0-15 minutes. Control variables include: age, age-squared, gender, health status, marital status, education, race dummies (3), occupational sector dummies (35), regional dummies (19), Goldthorpe social class (12), and wave dummies (18).

Table 2: Generalized ordered probit job satisfaction equation with random effects

Dependent variable: Overall job satisfaction	RE-GOPROBIT					
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6
Log of real pay per month	0.263** [0.0380]	0.253** [0.0269]	0.222** [0.0210]	0.252** [0.0185]	0.190** [0.0163]	0.0136 [0.0199]
Job tenure	0.0299+ [0.0161]	-0.00284 [0.0115]	-0.0115 [0.00886]	-0.00601 [0.00766]	0.00734 [0.00662]	0.0197* [0.00834]
Job tenure^2	-0.00121 [0.00111]	0.000349 [0.000783]	9.97e-05 [0.000603]	-0.000405 [0.000523]	- [0.000452]	- [0.000574]
Firm size: 10-49 people	-0.0413 [0.0422]	-0.0394 [0.0303]	-0.0822** [0.0233]	-0.124** [0.0205]	-0.190** [0.0179]	-0.204** [0.0216]
Firm size 2: 50-499	-0.124** [0.0441]	-0.163** [0.0314]	-0.194** [0.0244]	-0.240** [0.0217]	-0.320** [0.0193]	-0.344** [0.0244]
Firm size 3: 500+	-0.145* [0.0574]	-0.216** [0.0400]	-0.178** [0.0313]	-0.228** [0.0278]	-0.291** [0.0249]	-0.293** [0.0328]
Pension scheme	0.0607 [0.113]	-0.0543 [0.0782]	-0.0710 [0.0626]	-0.208** [0.0532]	-0.248** [0.0479]	-0.120* [0.0575]
Union member	0.0674+ [0.0366]	0.00747 [0.0260]	-0.0222 [0.0200]	-0.0145 [0.0176]	-0.0243 [0.0156]	-0.0609** [0.0202]
Promotion opportunity	0.0306 [0.0579]	-0.0256 [0.0407]	-0.116** [0.0312]	-0.129** [0.0275]	-0.114** [0.0246]	-0.0327 [0.0346]
Permanent job	0.383** [0.0341]	0.395** [0.0232]	0.389** [0.0175]	0.388** [0.0154]	0.318** [0.0136]	0.244** [0.0183]
Commute: 16-30 minutes	0.0383 [0.0569]	0.143** [0.0407]	0.169** [0.0320]	0.186** [0.0283]	0.206** [0.0258]	0.119** [0.0337]
Commute:31-60 minutes	0.0132 [0.0334]	-0.0156 [0.0237]	-0.0241 [0.0185]	-0.0333* [0.0164]	-0.0393** [0.0146]	-0.0319+ [0.0190]
Commute: 61-90 minutes	0.0248 [0.0451]	-0.00815 [0.0311]	-0.0535* [0.0239]	-0.0648** [0.0213]	-0.0804** [0.0191]	-0.0672** [0.0257]
Commute: 91+ minutes	-0.0404 [0.0974]	-0.0742 [0.0662]	-0.186** [0.0488]	-0.170** [0.0441]	-0.198** [0.0398]	-0.179** [0.0597]
log of hours worked pw	0.168 [0.209]	-0.148 [0.106]	-0.224** [0.0784]	-0.265** [0.0694]	-0.101 [0.0627]	0.139+ [0.0824]
Self-employed	-0.458** [0.0515]	-0.505** [0.0371]	-0.487** [0.0286]	-0.483** [0.0250]	-0.418** [0.0218]	-0.232** [0.0256]

Note: N=72,724. Log likelihood = -99135.224. Also see Table 1.

Table 3: Generalized ordered probit job satisfaction equation with random effects and Mundlak transformations

Dependent variable: Overall job satisfaction	RE-GOPROBIT-Mundlak					
	θ_1	θ_2	θ_3	θ_4	θ_5	θ_6
Log of real pay per month	0.254** [0.0465]	0.243** [0.0319]	0.229** [0.0248]	0.268** [0.0215]	0.220** [0.0187]	0.0727** [0.0234]
Job tenure	0.0373* [0.0179]	0.00048 [0.0125]	-0.00798 [0.00952]	-0.000896 [0.00816]	0.0101 [0.00700]	0.0145 [0.00898]
Job tenure^2	-0.0024* [0.0012]	-0.00063 [0.0008]	-0.00076 [0.0007]	-0.00127* [0.000556]	-0.0025** [0.000478]	-0.0032** [0.000618]
Firm size: 10-49 people	-0.0163 [0.0525]	-0.0491 [0.0372]	-0.091** [0.0281]	-0.129** [0.0243]	-0.164** [0.0210]	-0.162** [0.0266]
Firm size 2: 50-499	-0.0921+ [0.0558]	-0.109** [0.0391]	-0.150** [0.0300]	-0.208** [0.0262]	-0.260** [0.0231]	-0.263** [0.0310]
Firm size 3: 500+	-0.0303 [0.0740]	-0.119* [0.0504]	-0.142** [0.0385]	-0.178** [0.0337]	-0.208** [0.0298]	-0.220** [0.0416]
Pension scheme	0.0826 [0.121]	0.0449 [0.0830]	0.00548 [0.0652]	-0.139* [0.0553]	-0.190** [0.0496]	-0.0722 [0.0601]
Union member	0.0610 [0.0449]	-0.0254 [0.0315]	-0.00998 [0.0237]	0.00878 [0.0206]	-0.00985 [0.0180]	-0.0263 [0.0241]
Promotion opportunity	-0.0310 [0.0725]	-0.0489 [0.0510]	-0.120** [0.0382]	-0.126** [0.0332]	-0.0881** [0.0293]	-0.0573 [0.0426]
Permanent job	0.435** [0.0408]	0.426** [0.0273]	0.424** [0.0202]	0.388** [0.0176]	0.302** [0.0154]	0.227** [0.0215]
Commute: 16-30 minutes	0.0305 [0.0688]	0.107* [0.0483]	0.114** [0.0377]	0.138** [0.0332]	0.184** [0.0301]	0.00367 [0.0407]
Commute:31-60 minutes	-0.00432 [0.0416]	-0.0437 [0.0295]	-0.0172 [0.0225]	-0.0201 [0.0197]	-0.00488 [0.0173]	0.0232 [0.0235]
Commute: 61-90 minutes	0.0108 [0.0570]	0.0176 [0.0395]	-0.0333 [0.0298]	-0.0501+ [0.0261]	-0.0319 [0.0231]	0.0170 [0.0327]
Commute: 91+ minutes	-0.114 [0.121]	-0.00156 [0.0798]	-0.179** [0.0576]	-0.166** [0.0512]	-0.161** [0.0453]	-0.0889 [0.0701]
log of hours worked pw	0.470+ [0.258]	0.00466 [0.124]	-0.145 [0.0923]	-0.231** [0.0805]	-0.105 [0.0708]	0.0181 [0.0969]
Self-employed	-0.449** [0.0523]	-0.507** [0.0375]	-0.480** [0.0287]	-0.483** [0.0251]	-0.425** [0.0218]	-0.252** [0.0257]

Note: N=72,724. Log likelihood = -98804.981. See Table 1. Additional control variables include within person averages of all selected job characteristics as specified in the above model.

Figures 2A-2C: Marginal probability effects of job characteristics on job satisfaction

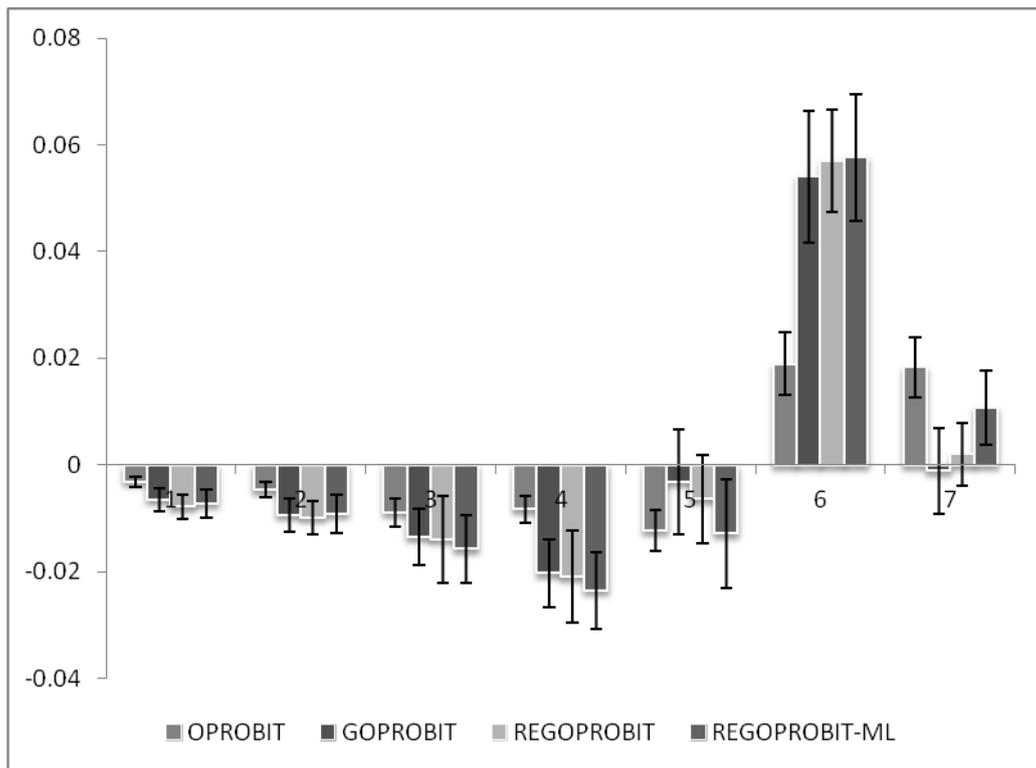


Figure 2A: log of pay per month

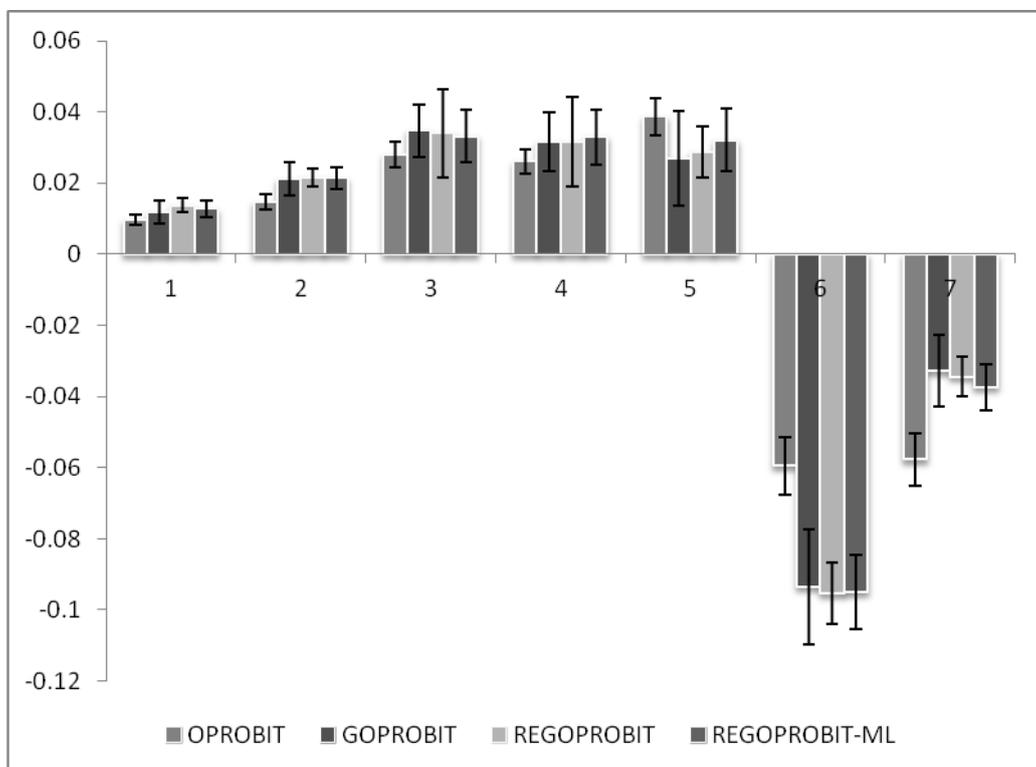


Figure 2B: log of hours worked per week

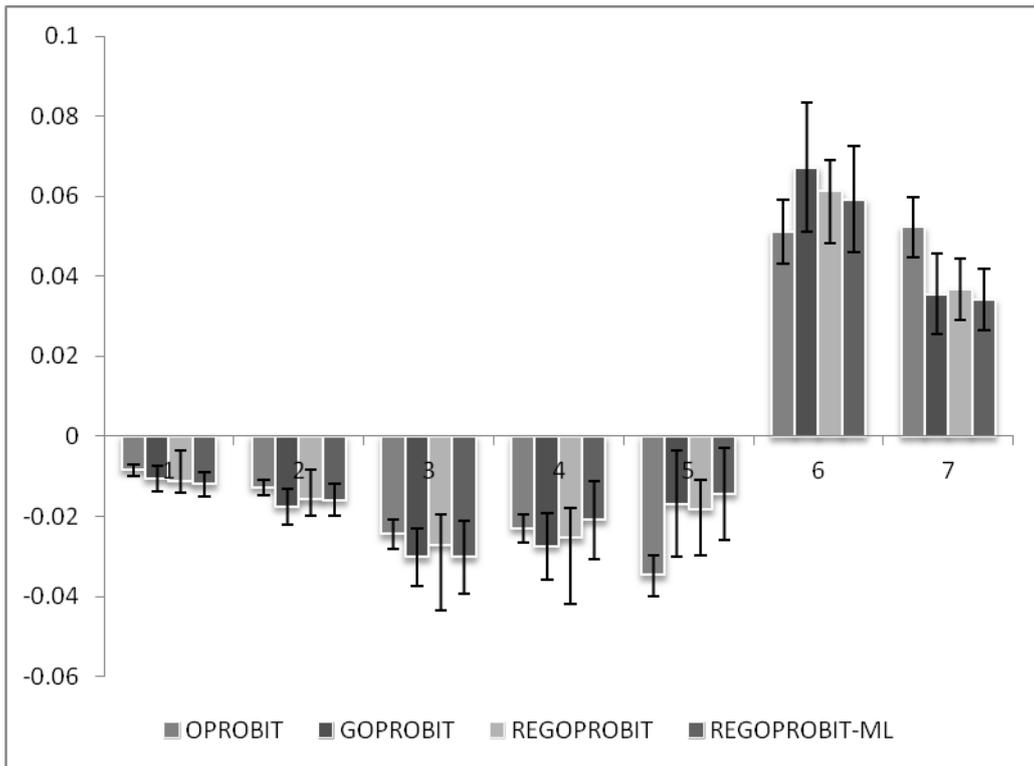


Figure 2C: promotion opportunities*

Note: * denotes the marginal probability effect of a dummy variable. 4-standard-error bars (two above, two below), i.e., 95% confidence interval. Marginal probability effects are estimated at the mean levels.

Figures 3A-3C: Trade-off ratios between variables

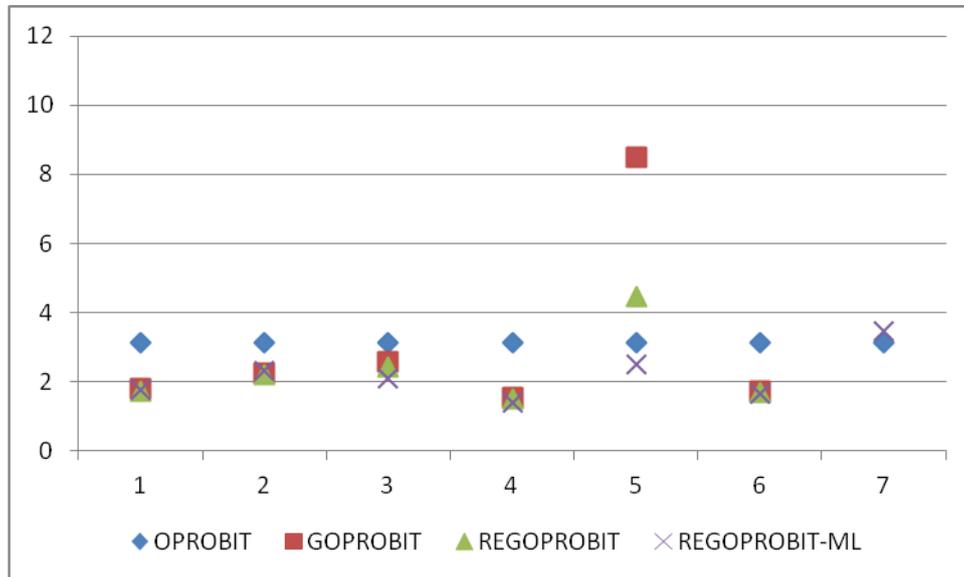


Figure 3A: How much additional pay per month (in %) is required to compensate a 1% increase in the number of hours work per week?

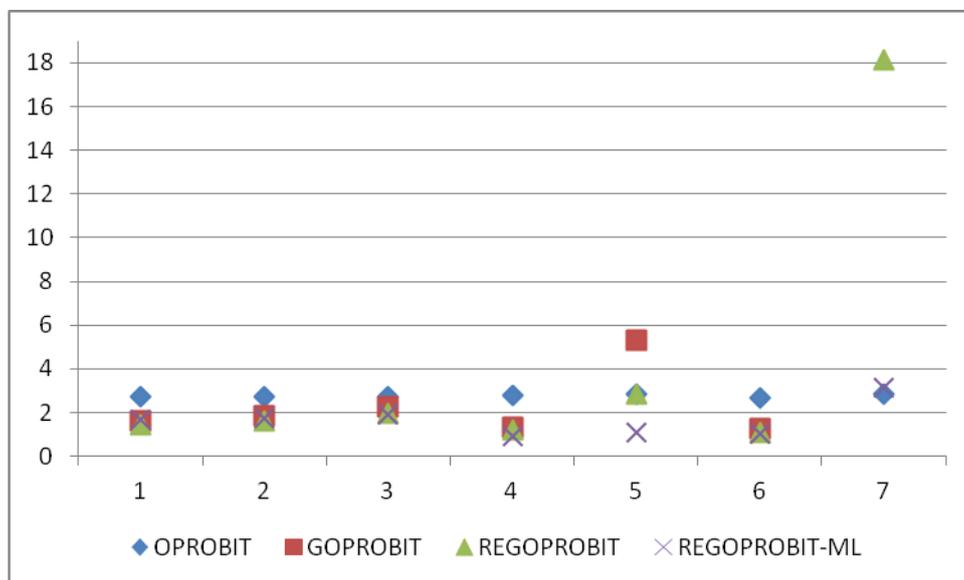


Figure 3B: How much additional pay per month (in %) is equivalent to having promotion opportunities at the workplace?

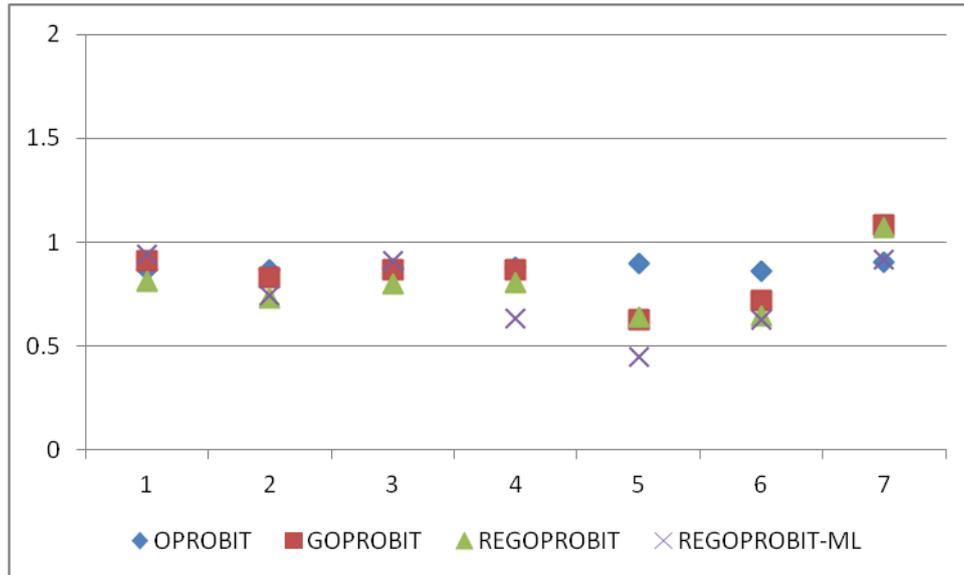


Figure 3C: How much work hours per week (in %) has to be reduced to compensate having no promotion opportunities at the workplace?

Table 1A: Descriptive Statistics

Main variables	M	STD
Job satisfaction	5.346	1.297
Log of real pay per month	6.820	0.839
Job tenure	10.280	4.615
Job tenure ²	126.998	67.718
Firm size: 10-49 people	0.298	0.458
Firm size 2: 50-499	0.341	0.474
Firm size 3: 500+	0.132	0.339
Pension scheme	0.545	0.498
Union member	0.124	0.329
Promotion opportunity	0.441	0.497
Permanent job	0.939	0.239
Commute: 16-30 minutes	0.284	0.451
Commute:31-60 minutes	0.154	0.360
Commute: 61-90 minutes	0.024	0.154
Commute: 91+ minutes	0.008	0.008
log of hours worked per week	3.445	0.487
Self-employed	0.004	0.066

Note: N=72,724.