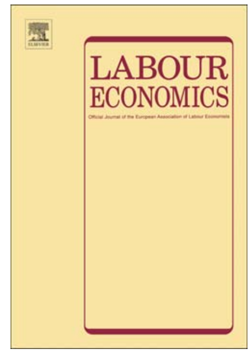

Wealth effects on job preferences

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PII: S0927-5371(15)00108-6
DOI: doi: 10.1016/j.labeco.2015.10.002
Reference: LABECO 1419

To appear in: *Labour Economics*

Received date: 7 April 2014
Revised date: 12 October 2015
Accepted date: 17 October 2015

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29th September 2015

Abstract

Preferences over jobs depend on wages and non-wage aspects. Variation in wealth may change the importance of income as a motivation for working. Higher wealth levels may make good non-wage characteristics relatively more important. This hypothesis is tested empirically using a reduced form search model in which differential job leaving rates identify willingness to pay for non-wage aspects of jobs. Marginal willingness to pay for non-wage aspects (measured by "job satisfaction for work in itself") is found to increase significantly after large windfall wealth gains in British panel data. Thus, wealth influences more than just the hours worked.

JEL: J21,J28,J32,J64

Keywords: labor supply; wealth; job satisfaction; duration models.

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1 Wealth and Labour Supply

Wealth inequality has is the subject of much debate in light of Piketty (2013). How do differences in wealth affect the labour market? Many studies examine a reduction in labour supply: workers substitute working with leisure (Henley (2004)), and unemployed individuals search longer for higher-paid jobs (Algan et al. (2003), Lentz and Tranaes (2005) and Lise (2013)). In all these models, job quality is a function only of the wage. This paper considers the influence of changing wealth levels on workers' labour supply in a model where workers are concerned about wages and non-wage characteristics with no attempt to identify what causes a job to have good non-wage characteristics. In the empirical part, reported "job satisfaction for work in itself" is used as an indicator of the value of non-wage aspects in a given job. British panel data reveals how workers' valuation of non-wage characteristics changes as a result of a wealth shock.

Identifying workers' valuation of non-wage characteristics is not trivial. If employers have to pay workers more to fulfill less satisfying tasks, it should be possible to recover preferences from wage differentials across jobs with different non-wage characteristics. However, Bonhomme and Jolivet (2009) find a "pervasive absence of compensating differentials". This may be due to informational deficiencies of firms (ignorant about workers' current preferences) and workers (ignorant about job offers, see Hwang et al. (1998)). Furthermore, legal and fairness constraints may prevent wage adjustments. As a result, jobs with better non-wage characteristics do not pay correspondingly lower wages, in line with the finding that high job satisfaction reduces turnover rates (Clark (2001)). Instead of using wage differentials to identify the value of non-wage characteristics, differential job quitting can be exploited. By observing the relative importance of differences in non-wage characteristics vis-à-vis wages in determining job leaving, it is possible to estimate workers' marginal willingness to pay (MWP) for physical working conditions (Gronberg and Reed (1994)), commuting distance (van Ommeren et al. (2000)) or the remaining duration of a contract (van Ommeren and Hazans (2008)). The approach allows an estimation of MWP, a structural preference parameter, in absence of a full structural model. We hypothesize that the MWP for non-wage characteristics increases with wealth: a diminishing marginal utility of consumption will imply a reduction in the relative importance given to wages whilst non-wage characteristics gain in importance when choosing a job. Thus an individual's change labour supply as a result of a change in wealth will depend on the balance of their job's wage and non-wage characteristics. Wealthier individuals are predicted to move away from jobs with poor non-wage characteristics. Since switching jobs takes time in a labour market with frictions, a change in preferences is best modelled as influencing workers' decisions to accept or reject job offers.

Increases in wealth result from savings, which may be derived from labour income, making identification of wealth effects on job preferences difficult. Thus, this article considers reactions to windfall gains (mainly from lottery winnings and inheritances). Since these windfalls are not related to labour market behaviour, they provide a source of identification for the effect of wealth on workers' job preferences. Windfall gains are used in other contexts (e.g. Imbens et al. (2001) and Kuhn et al. (2011) use US and Dutch lottery data). The impact of windfalls on the quantity of labour supply is studied by Henley (2004). Lindh and Ohlsson (1996) and Taylor (2001) study the effect of wealth on increasing self-employment. These studies do not discuss non-wage aspects of work. Taking non-wage dimensions into account allows us to explain the small overall reaction of hours and participation to changes in wealth. Whilst we have little to say about savings, trends in inheritance wealth suggest that our analysis is increasingly relevant to understand the labour market. Differences in unearned wealth may importantly influence the allocation of more or less satisfying jobs across individuals.

Section (2) presents a model to infer changes in MWP for non-wage characteristics from data on job leaving, adapting Gronberg and Reed (1994) to our context. Section (3) details our estimation of the determinants of job leaving with a focus on the estimators' treatment of heterogeneity and duration dependence. Section (4) presents the data. Section (5) provides evidence of changing job preferences by tracing the evolution of wages and job satisfaction for individuals who receive a windfall and subsequently change jobs. Section (6) estimates changes in MWP using all job leavers. Focusing on this larger set allows us to include the effect of wealth on transitions to non-participation in the analysis. Large changes in wealth, especially relative to income, are found to significantly increase MWP to pay for non-wage characteristics. Section (7) puts these findings into perspective and concludes.

2 A model of labour market responses to windfalls

Here we present a basic job search model and trace out how changes in assets can affect labour market behaviour. Workers care about consumption, c, non-wage characteristics, s, and not spending too much time searching, t^s. We assume that wealth is exogenous, disallowing wealth accumulation, so that all income is consumed. Thus we have that $c = m = r\ a + w$, where m is total income, w is labour income and $r\ a$ gives the returns to wealth.

Firms post job offers with fixed wages, w, and non-wage characteristics, s, that workers receive stochastically at Poisson rate $\lambda\, t^s$. The utility cost of search effort $e(t^s)$ is linearly additive in the utility function such that different job characteristics do not influence optimal search effort[1]. Once an offer is received, workers have perfect information about its characteristics[2]. We now allow workers to voluntarily leave the labour market. Assume that with some probability μ workers update their home production opportunities. Model this as a combination of material and other conditions m^h, s^h, valued by the same function $\psi(.)$ as in the labour market. Instantaneous utility can then be given as

$$\begin{aligned} u\,(c,s,e) &= \psi\,(w + r\,a, s) - e(t^s) \\ &= \psi\,(m,s) - e(t^s). \end{aligned} \tag{1}$$

Workers' acceptance strategies only depend on the instantaneous utility of their current job, since workers do not forego any option value by accepting an offer with higher instantaneous utility[3]: arrival rates of job offers and home production opportunities vary only by search intensity t^s and do not depend on employment status. Workers will move when the instantaneous utility of an offer exceeds the utility in their current job. By taking into account non-wage characteristics, the usual reservation wage is replaced by a reservation wage function $w^R(s)$. To proceed, note that if instantaneous utility fully describes the relative attractiveness of a job, it also determines expected returns to search. With this in mind, job leaving occurs either when workers are made redundant (at rate δ), when they receive an attractive home production opportunity (at rate $\mu\, \mathbb{1}\left[\psi(m^h,s^h) > \psi(m,s)\right]$), or when they receive a job offer whose value exceeds the value of their current job offer - with probability $\lambda\, t^s(\psi(a,w,s))\overline{F}(\psi(a,w,s))$, where $\overline{F}(.)$ is the inverse CDF of job vacancies. The overall rate of job quits $\theta(.)$ can then be given as

$$\theta(\psi(m,s)) = \delta + \mu\, \mathbb{1}\left[\psi(m^h,s^h) > \psi(m,s)\right] + \lambda\, t^{s*}(\psi(m,s))\, \overline{F}(\psi(m,s)).$$

[1]Including search effort in models with two-dimensional jobs is not trivial. If search costs are monetary, or time is valued at the wage rate, the instantaneous utility of a job is no longer the only way in which wage levels influence job leaving, creating problems for our identification strategy. van Ommeren et al. (2000) overcome this issue with an additive linear specification of utility, but this removes the role that diminishing marginal utility of money may play in increasing demand for non-wage characteristics at higher wealth levels. Instead, we assume that search takes time.

[2]Gielen (2013) shows that "learning about jobs" is not a major determinant of transitions.

[3]This excludes the cases where workers renegotiate their contracts or firms match workers' outside offers. In this case not only the instantaneous utility of a job would be of interest, but firms' ability to match future offers (see e.g. Postel-Vinay and Robin (2002)).

The rate of job leaving depends on the non-wage characteristics of the current job and on the current wage. Using $m = r\, a + w$,

$$\frac{\partial \theta}{\partial s} = \frac{\partial \psi}{\partial s}\left[\mu\, \frac{\partial Pr\left[\psi(m^h, s^h) > \psi(m,s)\right]}{\partial \psi(m,s)} + \frac{dt^{s*}}{d\psi}\, \lambda \overline{F}(\psi) + \frac{d\overline{F}(\psi)}{d\psi} \lambda\, t^{s*}(\psi(m,s))\right]$$

$$\frac{\partial \theta}{\partial w} = \frac{\partial \psi}{\partial m}\left[\mu\, \frac{\partial Pr\left[\psi(m^h, s^h) > \psi(m,s)\right]}{\partial \psi(m,s)} + \frac{dt^{s*}}{d\psi}\, \lambda \overline{F}(\psi) + \frac{d\overline{F}(\psi)}{d\psi} \lambda\, t^{s*}(\psi(m,s))\right].$$

These expressions can be combined to give equation (2). As in Gronberg and Reed (1994), we find that observing the relative weight of determinants of the observed job leaving rate (on the left-hand-side) is informative of the marginal rate of substitution between earnings and non-wage characteristics, i.e. the MWP for non-wage characteristics s (on the right-hand side),

$$\frac{\partial \theta / \partial s}{\partial \theta / \partial w} = \frac{\partial \psi / \partial s}{\partial \psi / \partial m}. \tag{2}$$

We can then show under which conditions changes in wealth influence the MWP for non-wage characteristics:

$$\begin{aligned} \frac{\partial}{\partial a}\left[\frac{\partial \theta / \partial s}{\partial \theta / \partial w}\right] &= \frac{\partial}{\partial a}\left[\frac{\partial \psi / \partial s}{\partial \psi / \partial m}\right] \\ &= \frac{\psi_{sm}\, \psi_m \;-\; \psi_{mm}\, \psi_s}{\left[\psi_m\right]^2}. \end{aligned} \tag{3}$$

Under standard assumptions about the form of the monetary utility function (diminishing marginal utility of income), expression (3) is positive. Extra income is less important to wealthier individuals. Consider an additive specification $\psi(m,s) = \psi_1(m) + \psi_2(s)$: then $\psi_{sm} = 0$ and as long as $\psi_{mm} < 0$, expression (3) will be positive. When might more wealthy individuals show *lower* marginal willingness to pay for non-wage characteristics? This would require $\psi_{sm} < \psi_{mm} \frac{\psi_s}{\psi_m}$, i.e. that the marginal utility of better non-wage characteristics falls very fast as wealth increases. However, most utility functions assume strategic complementarity, such that the cross-derivative is positive. In conclusion, if more "wealthy agents will be choosier" (Gomes et al. (2001)), their MWP should be higher. The following section shows how to test this prediction empirically and quantify the change in MWP for an exogenous change in wealth. Can we extend this framework to allow for endogenous capital accumulation following Lise (2013)? Unfortunately, it is then no longer innocuous to accept a job with higher instantaneous utility: in order to build up assets for the future, individuals may accept a job with a lower instantaneous utility.

3 Empirical Strategy

In this section we show how to exploit changes in the determinants of the job leaving rate before and after windfall wealth gains to estimate changes in MWP for non-wage characteristics following equation (2). Given that we do not have the precise dates for these windfalls, we cannot implement a timing of events framework à la Abbring and van den Berg (2003), and rely on the exogeneity of windfall wealth gains as key identifying strategy. Section (2) outlined the reasons for the stationarity of the optimal search strategy in our framework: workers compare their current job to job offers and home production opportunities arriving at a Poisson rate. This implies a proportional hazard rate of job leaving, which we estimate (without differentiating by destinations of job leavers) using panel data on windfalls, job durations, wages and job satisfaction.

We present two estimation methods that differ in how they treat duration dependence and individual unobserved heterogeneity. Using a mixed proportional hazard (MPH) specification, unobservables and observables x (individual characteristics - age, education, marital situation - as well as work-specific characteristics - part-time work, industry dummies etc.) enter multiplicatively in the hazard[4]. For job spell $j \in \{1, ..., J\}$ of individual i we then have

$$\theta_j = \theta_0(t)\ exp(\underline{x_j}\ \underline{\beta} + \eta_{i(j)}), \tag{4}$$

where $\underline{x}_j\ \underline{\beta} = \beta_w\ w_j + \beta_s\ s_j + \underline{x}_{0j}\ \underline{\beta_3}$, $\eta_{i(j)}$ is an individual unobservable effect and $\theta_0(t)$ is the baseline hazard allowing for duration dependence. Our focus is on the change in the coefficients β_w and β_s as a result of the wealth shock.

In the simplest version of this model, we assume a constant baseline hazard such that, conditional on the individual effect, the density of duration of spell j for individual $i(j)$ follows a negative exponential distribution with parameter θ_j,

$$f_j(t_j, \underline{x}_j | \underline{\beta}, \eta) = exp(\underline{x}_j\ \underline{\beta} + \eta_{i(j)})\ exp(-t_j\ exp(\underline{x}_{i(j),j}\ \underline{\beta} + \eta_{i(j)})). \tag{5}$$

Our estimation strategies part from this basic model by allowing for more flexibility in duration dependence and unobserved heterogeneity[5].

[4] This very common assumption implies that only current values of the covariates $\underline{x}$ influence the hazard rate. It is necessary in order to derive the MWP for non-wage characteristics from the estimated coefficients.

[5] Results for this basic exponential model (integrating out the unobserved heterogeneity term in equation (5) as in expression (8)) are not presented here, but are similar.

3.1 Heterogeneity

Unobserved differences across individuals are a particular issue in duration models since they create apparent duration dependence: the most frail individuals have a higher quit rate and thus on average shorter duration t, generating a decreasing hazard rate over duration (see van den Berg (2001)). We try to minimise the risk of misspecification due to individual heterogeneity.

First, in a Cox partial likelihood model we allow for gamma-distributed individual effects. Abbring and van den Berg (2007) show that unobserved heterogeneity satisfying the MPH assumption converges relatively fast to a gamma distribution in the survivor population, providing a justification for this functional form.

Second, since random effects models may nevertheless be sensitive to parametric restrictions, we estimate a second model allowing for a multinomial discrete distribution of heterogeneity following Heckman and Singer (1984).

Third, we restrict our sample to individuals for which we have at least two spells of employment. van den Berg (2001) shows that the potential for misspecification is much less severe in this case.

Fourth, we focus only on individuals who at some time in the sample receive a wealth shock. This ensures consistent results even if the population of individuals unexpectedly winning the lottery or inheriting wealth is different from those who do not play the lottery and do not inherit (appendix (A) reviews the representativeness of windfall recipients). This framework is akin to estimating an "effect of treatment on the treated", where unobserved heterogeneity is unlikely to be driving observed labour market reactions to wealth shocks.

3.2 Cox partial likelihood

The Cox partial likelihood model (CPL) allows for a flexible form of duration dependence - any multiplicative time-dependent baseline hazard rate is acceptable. The procedure is semi-parametric since the baseline hazard (θ_0 in (4)) is not estimated and the partial likelihood estimates of the coefficients ($\underline{\beta}$) are nonetheless consistent. Defining $\xi_i \equiv exp(\eta_i)$, the hazard rate can be given as

$$\theta_j(t_j|\underline{x}_j) = \theta_0(t_j)\ \theta_1(\underline{x}_j)\ \xi_{i(j)}, \tag{6}$$

where $\theta_1(.)$ is the "structural" part of the hazard rate. The intuition for the partial likelihood is to use the conditional probability that job spell j ends for a given risk set R^j (defined as the set of spells ending at or after j). Due to the proportional hazard assumption, the baseline hazard then drops out. We thus write the individual partial likelihood conditional on the individual effects as

$$L_i^{PL}(\underline{\beta}|t_{j=1...J}, \underline{x}_{j=1...J}) = \prod_{j=1}^{j=J} \frac{\theta_1(\underline{x}_j)\ \xi_{i(j)}}{\sum_{r\in R^j} \theta_1(\underline{x}_r)\xi_{i(r)}}. \quad (7)$$

The CPL model buys semiparametric identification at the cost of efficiency: only the ordering of job durations influences the likelihood, not the precise timing (t does not feature in expression (7)). For ξ we follow a parametric route and assume $\xi \stackrel{D}{\to} Gamma$. We use multiple observations per individual and integrate out individual effects such that individual likelihood contributions are given by

$$L_i(\underline{\beta}|t_{j=1...J(i)}, \underline{x}_{j=1...J(i)}) = \int_{-\infty}^{\infty} \prod_{j=1}^{j=J(i)} f_j(t_j, \underline{x}_j|r_i)d\, G_\xi(r), \quad (8)$$

with $f_j(t_j, \underline{x}_j)$ defined as in equation (5).

3.3 Multinomial random effects / Heckman-Singer

Whilst the non-parametric baseline hazard of the CPL model allows for unspecified duration dependence, this section focuses on the flexible specification of unobserved heterogeneity following Heckman and Singer (1984). In their semiparametric model[6], K groups in the population have different values of the unobserved heterogeneity term η (see equation (4)). The appropriate distribution $G_\xi(.)$ is then multinomial discrete across individuals i, where ξ is unchanging across spells $j \in \{1, ..., J(i)\}$. Individual i's likelihood contribution then takes into account the expectation of i belonging to group $k \in \{1, ..., K\}$, such that

$$L_i(\underline{\beta}|t_{j=1...J(i)}, \underline{x}_{j=1...J(i)}) = \sum_{k=1}^{k=K} p_k \prod_{j=1}^{j=J(i)} f_j(t_j, \underline{x}_j|\eta_k). \quad (9)$$

We use a piecewise linear specification for duration dependence to take into account the fact that (even controlling for heterogeneity) hazard rates may change over spell duration. The baseline hazard $\theta_0(t)$ is then a step function constant over discrete time periods. We use the following intervals: (i) less than one year; (ii) one to two years; (iii) two to four years; (iv) four to eight years; and (v) eight years or more[7].

[6]The method is *semi*parametric since inference is subject to a fixed number of groups. The common estimation procedure - followed here - is to augment the number of groups until the value of the likelihood function does not significantly increase any longer.

[7]These categories correspond approximately to the quintiles of the survival distribution.

4 Data

Since 1991, the British Household Panel Survey conducts yearly interviews of around 10,000 persons who are largely representative of the British population. To maintain overall sample size and representativeness despite attrition, new individuals are regularly included in the survey and followed indefinitely. All relevant variables for estimation are available for waves 5 and 7-18 (corresponding to years 1996, 1998-2010)[8]. To avoid comparing individuals who may be systematically different (on unobserved dimensions), we restrict our sample to individuals observed at least twice and who receive a windfall at least once during the sample period. We use respondents' labour market history, earnings, subjective job satisfaction, windfall receipt as well as numerous demographic controls. Since we do not model differential job leaving to retirement, we restrict the sample to ages 16-50. This leaves us with 10,937 job spells from 3,752 workers. Although our estimation sample is more likely to be married, male and in full-time employment than individuals who do not receive windfalls, the differences are not striking, as appendix (A) shows.

4.1 Jobs, sampling and attrition

We define duration in a job as duration with the same employer, since opportunities for job changes with the same employer are probably governed by different job offer arrival rates. Where there are several observations of job characteristics for one job, we use the most recent observation, since this is most relevant for the decision to leave a job[9]. Since we cannot use job spells for which we have no corresponding survey information, sampling occurs with decreasing probability as a function of job spell length. The issue of stock sampling is particularly relevant for the first wave of the sample, which only includes information about spells surviving until this date. We condition on survival until the first observation of any spell[10]. As outlined in section (3.1), we only consider individuals with multiple observations in the data: we have exact spell dates on an average of 2.8 jobs per worker.

[8]Lynn (2006) provides a detailed discussion of various aspects of the BHPS, while Jenkins (2010) gives an update focusing on the labour market and income dimensions.

[9]We implemented robustness checks for both assumptions: (a) including job mobility within a firm; and (b) using mean values of job satisfaction instead of the most recent evaluations. Results are similar.

[10]Dynamic selection via individual heterogeneity is not taken into account in this treatment. van den Berg and Drepper (2015) discuss that this biases coefficient values downward. As a robustness check, we excluded varying sets of left-truncated spells. Results are very similar.

Sample attrition is considerable (see table (3)), but a large fraction of spells are censored with the most recent wave of the sample. Given that censoring here is inevitable, it is unlikely these spells are systematically different from others[11]. Also, most censored spells concern individuals for who we have uncensored spells, such that individual characteristics are similar. In line with several studies of the BHPS finding that attrition does not influence results substantively (e.g. Cappellari and Jenkins (2004), Crouchley et al. (2007), Cappellari and Jenkins (2008)), we assume random attrition for censored spells.

4.2 Non-wage characteristics and job satisfaction

We require information on the non-wage characteristics of a job which is not influenced by the wage[12]. This excludes comprehensive evaluations of job quality such as “How satisfied are you with your job?”.

We focus on “job satisfaction for work in itself” as a measure for workers' appreciation of the non-wage aspects of a job. There are other questions relating to satisfaction with hours and job security (see table (1)), these dimensions of non-wage characteristics are less obvious to interpret however: the concept “job satisfaction with hours” is most obviously understood as an indicator of the distance between desired hours and actual hours - both of which may be affected by the wealth shock. Whilst job security is arguably a non-wage characteristic, our method is rather inappropriate to evaluate the MWP for job security. Individuals leaving workplaces with low job security may be a sign of imminent involuntary job loss and not revealed preference for job security. Job satisfaction with work in itself appears a good summary measure of the quality of fixed non-wage aspects specific to a job. In what follows, we thus refer to “job satisfaction for work in itself” simply as “job satisfaction”.

Reported job satisfaction may include an important subjective component - the same job may be viewed as satisfying by one person and not by another. This is acceptable as long as the subjective element is uncorrelated with wealth shocks and other covariates. We can then rephrase our research question as follows: “How

[11]Note also that unlike a competing risks framework, our single-destination estimation framework does not differentiate between different causes of involuntary transitions and censoring. On investigating censored spells, we find that - if anything - these spells have more attractive characteristics, making voluntary quits unlikely.

[12]This condition is not easily testable, since our theory suggests that non-wage characteristics and wages are correlated in the set of accepted jobs as a result of their substitutability in workers' utility function. The presence of a specific question related to satisfaction with financial rewards is reassuring in this context.

Table 1: Measures of job satisfaction

	Mean	Standard deviation	Min	Max
Job Satisfaction overall	5.182	1.363	1	7
Satisfaction with pay	4.829	1.794	1	7
Satisfaction with job security	5.315	1.552	1	7
Satisfaction with work in itself	5.289	1.371	1	7
Satisfaction with working hours	5.088	1.427	1	7

The precise question is: "I'm going to read out a list of various aspects of jobs, and after each one I'd like you to tell me from this card which number best describes how satisfied or dissatisfied you are with that particular aspect of your own present job." Answers range from "1- Not satisfied" to "4-Not Satisfied, not dissatisfied" and "7-Completely Satisfied".

does the influence of self-reported job satisfaction on job choice change over different wealth levels?"

4.3 Windfalls

We focus on windfalls from lottery and gambling winnings, inheritances, life and accident insurance payouts[13]. We assume that conditional on receiving a windfall, the timing and amount of the windfall are random. This ensures that no behavioural changes can be made prior to the windfall and that individuals with large windfalls are representative of the overall sample. We have no information on the exact date of the windfall and assume windfalls occur at the beginning of the period between interview dates - any other assumption would violate the no-anticipation assumption in some cases. For example, if a worker reports having received a windfall in the preceding period and also reports job mobility, we assume that the windfall occurred before the move.

Many windfalls are modest (with a median of £100[14]), especially those from lottery winnings and gambling. By contrast, payouts from accident insurance (£237), life insurance (£584), and especially inheritances (£2,294) are on average more substantial, as table (2) shows. Indeed, a significant fraction of windfalls

[13]Note that many windfalls originate in betting and lottery playing. This is a much more common practice in the UK than in many other countries, with apparently up to two thirds of the population engaged in gambling and over 57% playing the lottery (Clark and Apouey (2015)).

[14]All monetary values provided are deflated to their values in 2000.

Table 2: Size of windfalls received

in pounds	Inherit.	Lottery	Life ins.	Accident ins.	Total
1-1,000	98	2255	50	41	2695
1,000-5,000	158	78	198	148	627
5,000-10,000	79	8	32	23	149
10,000-50,000	115	2	42	11	183
50,000+	35	1	5	1	49
in % of earnings					
1-10 percent	141	2264	78	61	2,788
10-50 percent	153	69	184	122	578
50-100 percent	67	8	29	29	139
100+ percent	124	3	36	12	198

Note: for wave 5 only aggregate data are available - included in total.

exceeds annual earnings, as the lower panel indicates.

4.4 Wealth shocks and transitions

In the model presented above, changing levels of wealth may influence job-to-job transitions as well as transitions to non-participation (to have a baby, to care for family members, to move house or to take up full-time education). In our estimations presented in section (6), we thus include both of these (potentially) voluntary transitions in our analysis of job leaving. A robustness check revealed that including clearly involuntary job separations does not significantly modify results. Section (5) presents evidence of wealth effects on job preferences based on job-to-job transitions for which we can contrast job characteristics before and after the move.

Descriptive evidence of the impact of wealth shocks on job leaving rates is presented in figure (1), which gives the smoothed hazard rate out of the first 100 months of employment by receipt of a significant windfall (defined as a windfall greater than £2,000) and by job satisfaction (high job satisfaction defined as jobs with which workers are “nearly completely” or “completely” satisfied). Quit rates are highest for the group of windfall recipients with low levels of job satisfaction and lowest (over most of the job duration) for windfall recipients with high job

Table 3: Transitions

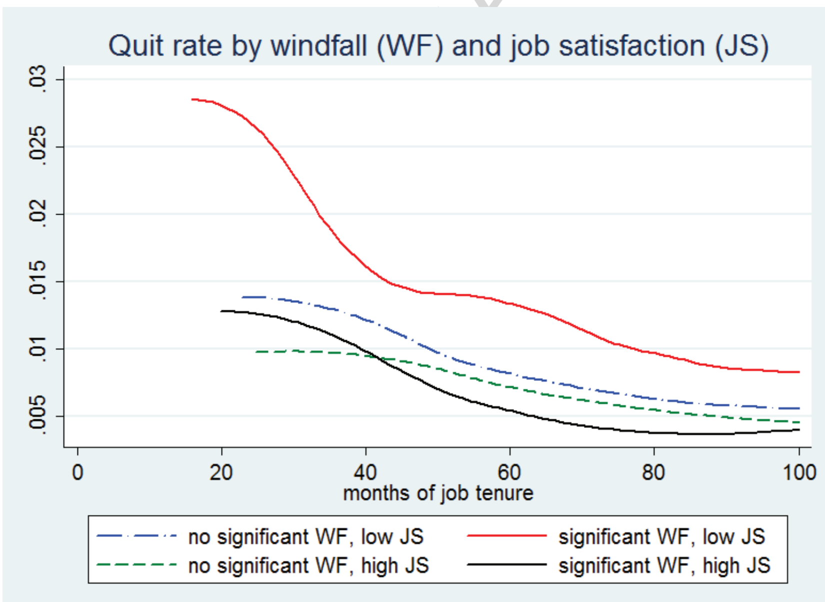
	number of spells	percent
job-to-job transition	1,884	16.47
left to have baby / children / care	209	1.91
moved area / to full-time education	1,411	12.90
dismissed / sacked / made redundant	1,005	9.19
early retirement	12	0.11
health reasons	128	1.17
censored	6,288	57.49
total	10,937	100

satisfaction. This suggests that labour supply effects of wealth may depend importantly on non-wage characteristics and provides a starting point for an answer to our research question: do changes in wealth influence the demand for more satisfying jobs? In section (5) we first consider the subset of transitions that are followed by another job observed in the data. We compare the jobs individuals *move from* to those they *move to*, and hence need not worry about differences in characteristics across individuals. We then consider all voluntary job leaving in section (6). Since this requires comparisons across different individuals, this section controls for observable and unobservable differences across individuals using the techniques outlined in section (3).

5 Job-to-job transition evidence

Before presenting results on job leaving determinants and MWP, this section considers the subset of job leaving which concerns job-to-job transitions. These transitions can provide valuable evidence concerning our basic hypothesis: we predict that the evolution of wages and job satisfaction will be systematically different for those individuals who have benefited from a windfall than for other job movers. Since we restrict ourselves to individuals who receive a windfall at some point during the sample period, we are comparing behaviour before and after windfall receipt. Unfortunately, we do not know the exact date windfalls are received, which restricts our sample to individuals who we observe over a three-year period: we compare job characteristics in the year preceding the windfall to job characteristics in a new job in the year after windfall and job change occurred - omitting the year in which windfall and job transition occurred, since we do not know the ordering of

Figure 1: Job leaving by windfall and job satisfaction
Significant windfall defined as windfall greater than £2,000



these events. This leaves us with few observations, making this section essentially descriptive.

We document the unconditional evolution of job satisfaction and wage earnings of 467 individuals (making 506 transitions) who received a significant windfall, changed jobs and for who we have information on origin and destination jobs. Obvious comparison groups are, first, the 1,714 persons (2,214 transitions) who received a significant windfall of at least £2,000 but did not move jobs. Second, the 3,088 individuals (6,190 transitions) who move jobs but did not receive any windfall.

If windfalls influence job leaving rates differentially depending on levels of job satisfaction, we should expect job satisfaction to increase more (and wages less) for those individuals who change jobs after a wealth windfall than for people moving jobs without receiving a windfall. Windfalls also enable satisfied workers to stay in their jobs and thus we also present non-movers who received a windfall. We deduct trend wage growth from the evolution of wages in figure (3)[15].

Concerning job satisfaction, figure (2) finds, first, significant increases in job satisfaction for job changes after windfall receipt (right panel), larger than those for job changes not preceded by windfall receipt (central panel). Job satisfaction does not increase in absence of a job change (left panel). Second, we can note that the level of job satisfaction is highest for individuals who receive a windfall and do not move, and lowest for individuals who move after a windfall, consistent with the idea that wealth enables workers to quit jobs with poor non-wage characteristics.

Figure (3) gives the evolution of yearly wages for individuals who receive a windfall and do not move (left panel), individuals who move jobs without having received a windfall (central panel) and individuals who move after receiving a windfall. The most obvious finding is that people who did not receive a windfall are moving away from badly paid jobs. This group benefits from significant earnings increases (over 10%). By contrast, individuals who move after windfall receipt do not benefit from significant wage increases. This is consistent with the idea that individuals who have received a windfall are less interested in increasing their wage when transiting from one job to another. How can we explain that individuals who do not change jobs after a windfall receipt see their wages increase

[15]Note that this corresponds to the evolution of the missing fourth group ("no windfall, no job mobility"), explaining why this group is omitted from figures (2) and (3). We also de-trend the values for job satisfaction in figure (2), but this makes no difference as job satisfaction levels evolve very little in jobs.

Figure 2: Evolution of mean job satisfaction for three types of transition (with 95% confidence interval)

"Job change" observations concern workers who quit and are observed in a new job.

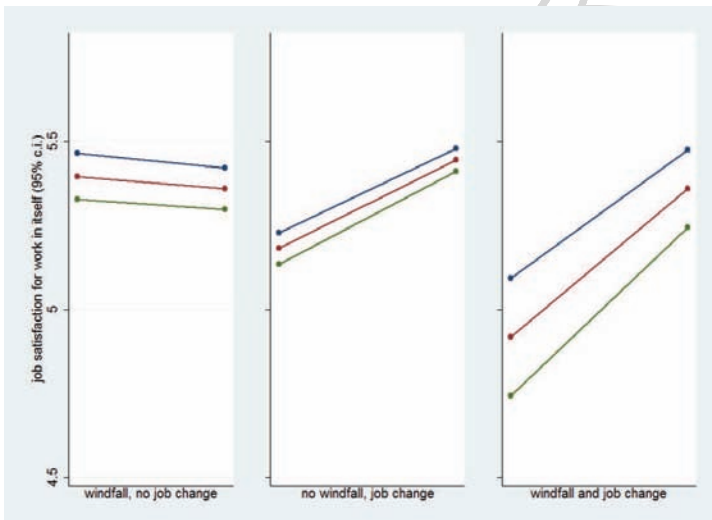
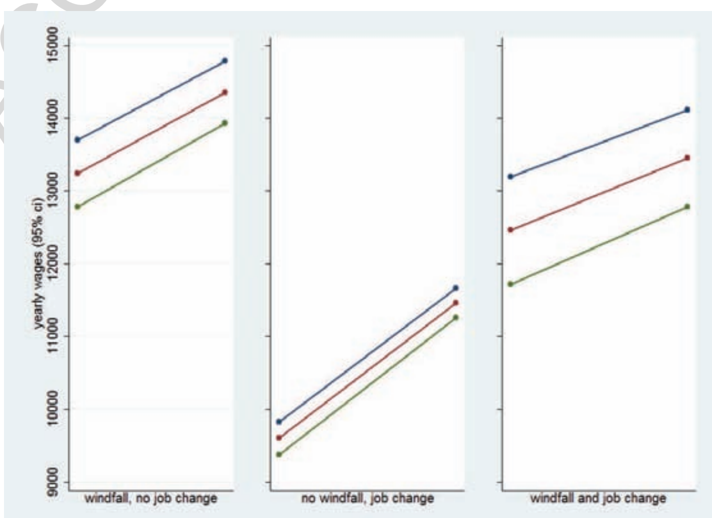


Figure 3: Evolution of mean wages for three types of transition controlling for wage growth (with 95% confidence interval)

"Job change" observations concern workers who quit and are observed in a new job. Figures are detrended by wage growth between observations points in a job with no windfall.



(marginally significant)? This may be a result of a selection process, whereby some newly wealthy individuals only stay at their job if they have good promotion prospects. This selection effect can also explain why the wage level of windfall recipients amongst job-to-job transitions is significantly higher than among other job movers: some workers in badly paid jobs may quit and leave to unemployment or non-employment.

In summary, the evidence on transitions is consistent with the idea that workers whose wealth suddenly increases become more sensitive to non-wage factors when choosing jobs.

6 Estimation results

This section presents estimates of the change in job preferences as a result of increases in wealth levels based on differential job leaving probabilities and reviews their economic interpretation. We do not have enough observations to differentiate between destinations in a competing risks framework, instead focusing on job leaving. To derive MWP estimates we then estimate changes in the determinants of job leaving. This captures changes in job quitting to non-participation as well as job-to-job transitions where we lack information on the new job's characteristics. This strategy is particularly appropriate to assess the total size of the effect of wealth on job preferences, i.e. the change in MWP for non-wage characteristics.

Tables (4) and (5) present estimated determinants of job leaving using the estimators discussed in section (3). These tables focus on the key ingredients necessary to derive the MWP. Full results tables including information on the numerous controls for individual characteristics on both observed and unobserved dimensions are relegated to appendix (B). Results for our key parameters are robust to assuming no observed or unobserved heterogeneity (not reported).

The estimates indicate, first, that in line with the initial hypothesis, the impact of windfalls on quitting is significantly less important for highly satisfied workers, i.e. that the interaction effect between job satisfaction and windfall receipts negatively affects job leaving probabilities[16]: labour supply effects of wealth depend on job satisfaction levels. For illustration, the predicted hazard rate at mean covari-

[16] Ai and Norton (2003) note that the cross-derivative we are interested in is not equal to the interaction effect in non-linear models. The interaction effect will vary over covariates in a non-linear model. In our case, marginal effects of interest were of the same sign at the median of the covariates.

ates doubles (from 0.02 to 0.04/month) for dissatisfied workers who receive a large windfall (one standard deviation above the mean windfall), while the hazard rates change very little for satisfied workers. These estimates imply that whilst 50% of dissatisfied workers leave their job within 18 months after a windfall, this figure is only reached after more than 4 years for satisfied workers.

Second, the wealth effect on demand for good jobs depends importantly on the size of the windfall. In table (4) the effect is shown using a quadratic windfall function. Comparing the coefficients on log windfall (LWF) and log windfall squared (LWF2), we find that the effect is increasing in windfall size. Furthermore, behavioural reactions to windfalls depend not on their absolute amount but on their amount relative to income. Table (5) shows that if windfalls are expressed as a percentage of annual income, only windfalls of over 50 percent of annual income lead to a behavioural reaction. For these windfalls we see again that the labour supply effect will depend importantly on job satisfaction, indicating the importance of non-wage characteristics in explaining job leaving. In fact, we find a significant change not only in the coefficient on job satisfaction, but also on wages, contrary to the previous two specifications, and reinforcing the effect of wealth on the MWP for job satisfaction.

Table 4: Determinants of job mobility with loglinear windfall function

	Cox PH $\hat{\beta}$ (s.e)	Heckman Singer $\hat{\beta}$ (s.e.)
Log Wage (LW)	-0.512***	-0.577***
	(0.057)	(0.052)
Job Satisfaction (JS)	-0.090***	-0.100***
	(0.017)	(0.016)
Log Windfall (LWF)	-0.463	-0.249
	(0.377)	(0.348)
Log Windfall squared (LWF^2)	0.078	0.036
	(0.048)	(0.043)
LWF*JS (interaction)	0.025	0.031**
	(0.016)	(0.015)
LWF^2*JS (interaction)	-0.005**	-0.004**
	(0.002)	(0.001)
LWF*LW (interaction)	0.031	0.010
	(0.039)	(0.036)
LWF^2*LW	-0.004	-0.001
	(0.005)	(0.004)

Dependent variable: hazard rate of job leaving. Sample size: $N = 3,752$;$N * J = 10,937$. Significance levels:10%(*),5%(**),0.1%(***) Controls: age,age^2,education,education^2, 3 industry dummies, 4 family situation dummies, working hours, part-time dummy;

Table 5: Determinants of job mobility with windfalls relative to income

	Cox PL	Heckman Singer
	$\hat{\beta}$ (s.e)	$\hat{\beta}$ (s.e)
Log Wage (LW)	-0.589***	-0.570***
	(0.053)	(0.049)
Job Satisfaction (JS)	-0.091***	-0.103***
	(0.017)	(0.016)
Windfall 0-10pct (W10pct)	0.184	-0.248
	(0.361)	(0.345)
Windfall 10-50pct (W50pct)	0.394	0.216
	(0.257)	(0.254)
Windfall 50+ pct (W50+pct)	0.488**	0.260
	(0.160)	(0.153)
JS*W10pct	0.028	0.055
	(0.036)	(0.033)
JS*W50pct	-0.001	-0.039
	(0.062)	(0.057)
JS*W50+pct	-0.300**	-0.192**
	(0.112)	(0.094)
LW*W10pct	-0.032	0.003
	(0.033)	(0.032)
LW*W50pct	-0.000	0.029
	(0.045)	(0.042)
LW*W50+pct	0.160**	0.107**
	(0.062)	(0.0535)

Dependent variable: hazard rate of job leaving. Sample size: $N = 3,752$;$N * J = 10,937$. Significance levels:10%(*),5%(**),0.1%(***) Controls: age,age^2,education,education^2, 3 industry dummies, 4 family situation dummies, working hours, part-time dummy;
Windfalls: W10pct: 1-10% of annual income; W50pct: 10-50% ; W50+pct: 50+%; Reference category:0%

Using the basic formulation in equation (2), we now use these estimated coefficients to assess how MWP changes after windfall gains. From equation (2), and noting that estimated coefficients refer to the log wage, we have

$$MWP = \frac{\tilde{\beta}_s}{\tilde{\beta}_w}\ w. \tag{10}$$

Concentrating first on the point estimates, we find a five-fold increase in the marginal willingness to pay for an additional point of job satisfaction (the standard deviation is 1.37) - from around $£2,000$ to over $£10,000$ for windfalls valued at over $£100,000$. Figure (4) sketches the implied marginal willingness to pay over a range of windfall values (based on simulations using the estimated coefficients from the Cox partial likelihood specification and mean values for the covariates).

Figure 4:

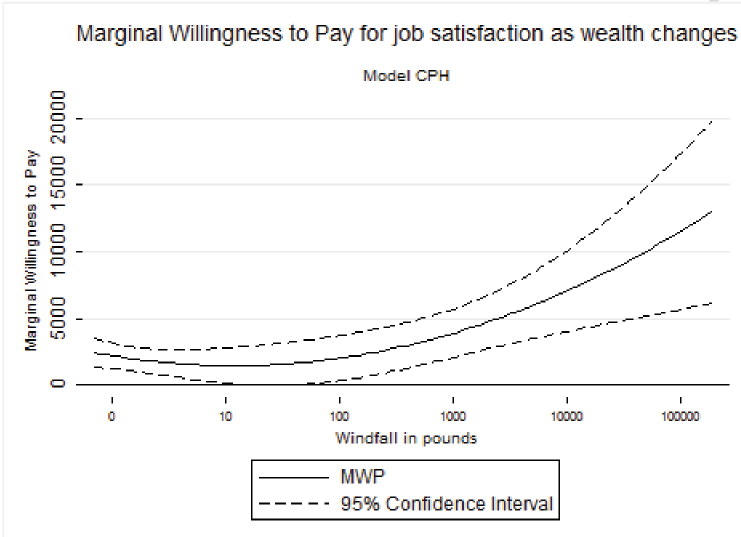


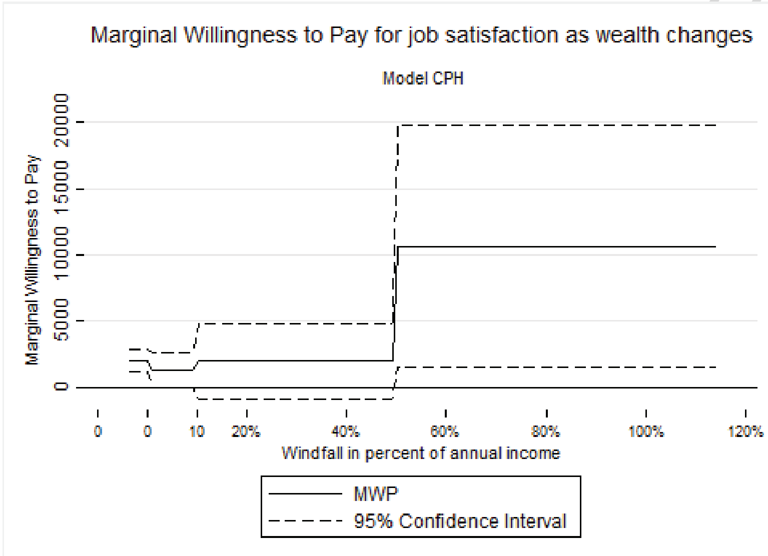
Figure (5) shows MWP as a function of windfalls expressed as a fraction of earnings.

Second, the precision of the estimates suggests some caution in the interpretation of the results[17]. We find that despite large increases in the point estimates, using the specification of windfalls as a percentage of earnings, changes in the marginal willingness to pay are not significant at the 5% level. Despite the large sample, the number of individuals affected by large windfalls remains small and limits inference.

Does this imply that few workers' job preferences are subject to wealth effects? Comparing several British data sources, Karagiannaki (2015) shows that around 10% of inheritances are valued at 100,000 pounds or more, with 43% of the British population inheriting at some point over the lifecycle. Different data sources concord in showing an increasing number especially of large inheritances, indicating that more individuals will be affected in the future.

[17]Standard errors are calculated using the delta method (based on a Taylor approximation), see Wooldridge (2002), p.44f.

Figure 5:



7 Conclusion

This paper focuses on the impact of wealth in a labour market characterized by search frictions, and where jobs contain wage and non-wage dimensions. Using British panel data, the demand for good non-wage characteristics in jobs is found to increase with wealth. The way in which the labour market distributes utility may depend importantly not only on human capital and luck (as in models of the labour market focusing on productivity and frictions) but also on wealth. Wealth is used to quit bad jobs and accept more satisfying jobs that are not necessarily better paid.

First evidence is found evaluating the job characteristics of job movers who had received a windfall: compared to other job movers, their earnings increased less and job satisfaction more. The increased demand for non-wage dimensions of jobs was quantified using the willingness to pay for jobs with higher "job satisfaction for work in itself". Before receiving a windfall, individuals are on average willing to forego annual earnings of $£2,000$ for a one-point increase in job satisfaction - after a large windfall this figure increases five-fold. Whilst the estimated MWP ($£10,000$) is somewhat imprecisely estimated, it represents a marginal propensity to consume job satisfaction out of the windfall gain of around 10%, which does not appear excessive. Changes in MWP are estimated to be important when windfalls are large in relation to earnings. Although transitions may be temporary, in a frictional labour market job moves may lead to persistent changes.

Why might increasing MWP for non-wage characteristics matter? First, groups and countries with higher earnings may also have higher wealth levels. Focusing only on earnings may then underestimate labor market inequality. Second, other groups with high levels of wealth (e.g. a creative class) may have larger utility levels of employment than members of groups with similar earnings but less wealth. Comparing income across groups may not reflect their labour market performance. Third, over time, increases in wealth and MWP for satisfying jobs may crowd out certain types of jobs. Finally, policy evaluations of labour taxes that contain income effects (e.g. changes to the average income tax rate) should take into account not only changes in the quantity of labour supplied but also changing job characteristics. Direct evidence of any of these effects based on comparisons of levels of earnings and job satisfaction across time and space are difficult: this would require comparing subjective evaluations made by very different groups, something this study avoids.

A Representativeness of windfall recipients

How representative are our findings of the overall population? Columns (I) and (II) of table (6) compare all workers under the age of 50 in the BHPS who receive a windfall at some point to those who do not. These columns include individuals for whom we do not have enough information for estimation. Albeit mostly statistically significant, differences in age, education, hours worked and wages, as well as industrial sector appear relatively small. By contrast, individuals reporting windfalls are less likely to be female and more likely to be married. Note that comparing time-varying characteristics is not obvious since individuals are in the panel for differing time periods. We here use first appearance in the panel.

Columns (III) and (IV) concern the more restrictive sample of workers from waves 5 and 7-18 for whom we have the necessary information to include them in estimation. We contrast our estimation sample (column (IV)) to individuals who are not in the sample for the sole reason that they did not receive a windfall (column (III)). The estimation sample appears to be weighted towards married men, with smaller (but still significant) differences in age, education, part-time working, hours per week and wages. Whilst the estimation is based only on individuals who receive windfalls (in the interest of avoiding unobserved specific characteristics of this group), the group does not appear to be too different from the overall BHPS sample. The preponderance of married men (for whom labour supply elasticities are small) suggests that, if anything, sensitivity of job leaving to wealth may be lower in the estimation sample.

Table 6: Representativeness of Sample

	All workers under 50			Estimation sample vs. non-windfall recipients		
	(I)	(II)		(III)	(IV)	
	received no windfall	received a windfall	difference	received no windfall	received a windfall	difference
female (pct)	55.61%	49.67%	***	58.02%	50.43%	***
age (years)	29.33	31.54	***	30.51	31.80	***
married (pct)	32.23%	44.03%	***	38.46%	48.66%	***
education (years)	10.95	11.02	n.s.	11.45	12.10	***
part-time (pct)	22.14%	19.73%	***	20.53%	17.16%	***
hours worked (p.w.)	33.81	34.35	**	34.27	34.89	**
log hourly wages	1.61	1.63	**	1.67	1.76	***
N	7,127	7,420		2,470	3,752	
wholesale & retail	17.93	17.29	n.s.	16.98	16.12	n.s.
manufacturing	13.05	15.70	**	15.29	19.99	***
health & social work	12.65	9.59	***	14.44	8.70	***
rent, realestate, consulting	9.52	11.27	**	7.81	10.87	**
hotel & restaurant	8.68	7.96	n.s.	5.86	4.67	n.s.
education	8.61	7.24	*	8.85	7.74	n.s.
N	4,054	2,210		1,537	1,886	

Notes: industry categories are only available for subset of workers - the six largest are given.
Significance levels: not significant (n.s.), 10%(*), 5%(**), 0.1%(***)
Columns (I) & (II): workers aged under 50 from waves 1-18.
Columns (III) & (IV): workers aged under 50 from waves 5,7-18 with multiple spells and no missing values on variables used in estimation. Note that the column (IV) consists of all individuals whose spells are used in estimation.

B Full Estimation Results

	(I) Cox PL	(II) Heckman Singer	(III) Cox PL	(IV) Heckman Singer
Log Wage (LW)	-0.512***	-0.577***	-0.589***	-0.570***
	(0.057)	(0.052)	(0.053)	(0.049)
Job Satisfaction (JS)	-0.090***	-0.100***	-0.091***	-0.103***
	(0.017)	(0.016)	(0.017)	(0.016)
Log Windfall (LWF)	-0.463	-0.249		
	(0.377)	(0.348)		
Log Windfall squared (LWF^2)	0.078	0.036		
	(0.048)	(0.043)		
Log Windfall & Job satisfaction (interaction)	0.025	0.031**		
	(0.016)	(0.015)		
Log Windfall squared & Job satisfaction (interaction)	-0.005**	-0.004**		
	(0.002)	(0.001)		
Log windfall & Log wage (interaction)	0.031	0.010		
	(0.039)	(0.036)		
Log windfall squared & log wage (interaction)	-0.004	-0.001		
	(0.005)	(0.004)		
Windfall 0-10pct (W10pct)			0.184	-0.248
			(0.361)	(0.345)
Windfall 10-50pct (W50pct)			0.394	0.216
			(0.257)	(0.254)
Windfall 50+ pct (W50+pct)			0.488**	0.260
			(0.160)	(0.153)
JS*W10pct			0.028	0.055
			(0.036)	(0.033)
JS*W50pct			-0.001	-0.039
			(0.062)	(0.057)
JS*W50+pct			-0.300**	-0.192**
			(0.112)	(0.094)
LW*W10pct			-0.032	0.003
			(0.033)	(0.032)
LW*W50pct			-0.000	0.029
			(0.045)	(0.042)
LW*W50+pct			0.160**	0.107**
			(0.062)	(0.0535)
Education	-0.114***	-0.105***	-0.107***	-0.106
	(0.020)	(0.018)	(0.020)	(0.018)
Education squared	0.006***	0.006***	0.006***	0.006
	(0.001)	(0.000)	(0.001)	(0.000)
Industry sector 1 (Primary)	-0.618***	-0.640***	-0.619***	-0.637***
	(0.129)	(0.123)	(0.129)	(0.123)
Industry sector 2 (Services)	-0.479***	-0.403***	-0.477***	-0.401***
	(0.050)	(0.047)	(0.050)	(0.047)
Industry sector 3 (Social & Political)	-0.777***	-0.733***	-0.783***	-0.735***
	(0.062)	(0.060)	(0.062)	(0.060)

table continued overleaf

table continued from above

	(I) Cox PL	(II) Heckman Singer	(III) Cox PL	(IV) Heckman Singer
Separated from Partner[2]	0.624***	0.502***	0.675***	0.505***
	(0.142)	(0.131)	(0.141)	(0.132)
Divorced	0.323***	0.471***	0.364***	0.470***
	(0.098)	(0.092)	(0.099)	(0.091)
Married	0.042	0.117**	0.449	0.111*
	(0.060)	(0.057)	(0.061)	(0.057)
Widowed	-0.058	0.114	0.031	0.114
	(0.313)	(0.295)	(0.312)	(0.296)
Hours	0.017***	0.016***	0.019***	0.016***
	(0.003)	(0.003)	(0.003)	(0.003)
Part-time (dummy)	0.158	0.148	0.206**	0.146
	(0.098)	(0.093)	(0.098)	(0.093)
Age (years)	-0.225***	-0.139***	-0.225***	-0.138***
	(0.023)	(0.021)	(0.023)	(0.021)
Age (years squared)	0.002***	0.001***	0.002***	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)
Tenure (<1 year)		0.097		0.751***
		(0.096)		(0.087)
Tenure ($1-2$ years)		0.589***		0.967***
		(0.083)		(0.075)
Tenure ($2-4$ years)		1.057***		1.209***
		(0.073)		(0.066)
Tenure ($4-8$ years)		0.712***		0.835***
		(0.072)		(0.067)
p_1		0.592***		0.584***
		(0.055)		(0.056)
p_2		0.407**		0.415**
		(0.135)		(0.135)
η_1 mass point		1.445***		1.448**
		(0.068)		(0.386)
η_2		0 (normalized)		0 (normalized)
ξ frailty variance	0.647***		0.702***	
	(0.055)		(0.058)	

Dependent variable: hazard rate of job leaving. Sample size: $N = 3488$;$N * S = 10386$
Significance levels: 10%(*), 5%(**), 0.1%(***)
Windfalls: W10pct: 1-10% of annual income; W50pct: 10-50%; W50+pct: 50+%; Reference category:0%. Industry sector 1: agriculture, mining, construction; Industry sector 2: wholesale, retail, transport, communications, finance, real estate; Industry sector 3: public administration, education, health, community & social work. Industry reference category: manufacturing. Tenure reference category: over 8 years. Family reference category: single.

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Highlights

- Labour supply reductions after a wealth shock depend on jobs' non-wage aspects
- Demand for non-wage aspects is measured using differential job leaving in Britain
- Wage and satisfaction are found to evolve differently when wealthy people move jobs
- Marginal Willingness to pay for job satisfaction increases for large windfall gains