Social Interactions in Job Satisfaction*

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Abstract

The literature documents that job satisfaction is positively correlated with worker performance and productivity. We examine whether aggregate job satisfaction in a certain labor market environment can have an impact on individual-level job satisfaction. If the answer is yes, then policies targeted to increase job satisfaction can increase productivity not only directly, but through spillover externalities too. We seek an answer to this question using two different datasets from the United Kingdom characterizing two different labor market environments: Workplace Employment Relations Survey (WERS) at the workplace level (i.e., narrowly defined worker groups) and British Household Panel Survey (BHPS) at the local labor market level (i.e., larger worker groups defined in industry × region cells). Implementing an original empirical strategy to identify spillover effects, we find that one standard deviation increase in aggregate job satisfaction leads to a 0.42 standard deviation increase in individual-level job satisfaction at the workplace level and 0.15 standard deviation increase in individual-level job satisfaction at the local labor market level. These social interactions effects are sizable and should not be ignored in assessing the effectiveness of the policies designed to improve job satisfaction.

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1 Introduction

Job satisfaction is a direct measure of utility an employed worker derives from his/her current job [Clark and Oswald (1996)]. It has extensive behavioral consequences. For example, job satisfaction is a significant determinant of labor market mobility—in particular, the quitting behavior.[1] It is also shown to be related to relative pay comparisons among peer groups in the workplace.[2] Most importantly, and this is mainly why labor economists should be interested in job satisfaction, it is documented to have a positive correlation with labor productivity and worker performance.[3] In particular, Boeckerman and Ilmakunnas (2012) document that job satisfaction has a causal effect on productivity.[4] To get the feel of the magnitude, Boeckerman and Ilmakunnas (2012) find that one standard deviation increase in job satisfaction within the plant increases productivity per hours worked by 6.6 percent.

Although several aspects of job satisfaction have been studied extensively in the empirical literature, whether there exist spillover externalities in job satisfaction—i.e., whether individual-level job satisfaction is affected by the aggregate job satisfaction in a certain labor market environment—or not remains as an unanswered question. This is a relevant question because job satisfaction is often associated with workplace attitudes such as involvement in the organization, relatedness with co-workers/customers/managers, attachment, motivation, shirking, tendency to slow down work, absenteeism, etc. These attitudes form a workplace "atmosphere" and jointly contribute to the formation of worker satisfaction and performance. Therefore, the aggregate job satisfaction level in a certain work environment can be regarded as a "social" variable and may, in turn, affect individual-level job satisfaction.

Our ultimate goal in this paper is to investigate if there exist any visible footprints of social interactions in job satisfaction. Answering this question is also important for policy. If there

[1] See, e.g., Freeman (1978), Akerlof et al. (1988), Clark et al. (1998), and Clark (2001).

[2] See, for example, Clark et al. (2009) and Card et al. (2012).

[3] Other studies documenting this positive relationship include, but are not limited to, Iaffaldano and Muchinsky (1985), Ostroff (1992), Brown and Peterson (1994), Ryan et al. (1996), Sloane and Williams (2000), Argyle (2001), Judge et al. (2001), Harter et al. (2002), Schneider et al. (2003), Patterson et al. (2004), Green and Tsitsianis (2005), Otis and Pelletier (2005), Christen et al. (2006), Ghinetti (2007), and Wegge et al. (2007). Zelenski et al. (2008) and Oswald et al. (2013) argue that happiness and life satisfaction are also positively correlated with productivity.

[4] The relationship between productivity and job satisfaction has been controversial in the literature due to causality. However, recent literature proves that the direction of the relationship goes from job satisfaction to labor productivity.

exist positive spillovers in job satisfaction, then policies targeted to increase job satisfaction can boost productivity not only directly, but through spillover externalities too. When these social interactions effects are sizable, ignoring them may lead to mis-assessment of the effectiveness of the policies designed to improve job satisfaction in various work environments.

We perform our empirical analysis at two aggregation levels using two different datasets from the United Kingdom. *First*, we use the Workplace Employment Relations Survey (WERS) to test the existence of job satisfaction spillovers at the workplace level (or establishment-level).[5] In the workplace-level analysis, the reference group that the social forces are effective is the set of workers in each workplace. *Second*, we use the British Household Panel Survey (BHPS) to form industry $\times$ region cells for the purpose of testing the existence of spillovers at the local labor market level. In this second exercise, we try to capture more general social effects in larger reference groups. The main purpose is to focus on social processes that involve collective aspects of community and work life. In both of these exercises, we concentrate on estimating the correlation between the group-level and individual-level job satisfaction scores, controlling for a large set of observed covariates. Drawing a distinction between the workplace and local labor market level analyses is useful, because it will allow us to make precise statements on whether it is more effective to enforce job satisfaction policies at the establishment level (i.e., as firm-specific policies) or local labor market level (i.e., in the form of broader institutional measures).

Our econometric framework will be a version of the canonical linear-in-means model, which is a base for the bulk of empirical work on social interactions.[6] The main problem with the linear-in-means model is that it necessitates employing a carefully-designed identification strategy to separate endogenous effects from the contextual effects [Manski (1993)]. It will perhaps be useful at this point to clearly define the terms "endogenous social effects" and "contextual social effects."[7] The endogenous effect refers to the effect of the group-level outcome on the

[5] The terms "workplace" and "establishment" will be used interchangeably throughout the paper.

[6] See Blume et al. (2011) for an in-depth background information on linear-in-means models, including a comprehensive discussion on microfoundations and econometric identification. Also see Blume and Durlauf (2001), Brock and Durlauf (2001b), and Soetevent (2006).

[7] See also Manski (2000) and Brock and Durlauf (2001b) for a more detailed discussion of the different types of social interactions effects.

individual-level outcome. Within the context of our paper, this corresponds to the effect of the group-level mean of job satisfaction on the individual-level job satisfaction. The contextual effect, on the other hand, refers to the effect of the group-level counterparts of the individual-level observables on the individual-level outcome variable; in our paper, this corresponds to the effect of, say, group-level average age or average education on the individual-level job satisfaction score.

At the center of our identification strategy lies an insight from the hierarchical (or multilevel) statistical models of social processes: social groups describe "ecologies" in which decisions are made and matter because different ecologies induce different mappings from the individual determinants of these decisions to the associated outcomes [Raudenbush and Sampson (1999)]. Based on this conceptualization, we construct an empirical model in which contextual effects (i.e., the "ecologies" in our model) alter the coefficients linking individual characteristics to outcomes. This corresponds to allowing for multiplicative interactions between the contextual effects and the remaining explanatory terms within the linear-in-means model. We formally show that introducing these cross-product terms induces nonlinearities that resolve the reflection problem Manski (1993) describes [see Section 3]. Such a setup secures the econometric identification of social interactions and enables us to separate endogenous effects from the contextual effects [Blume and Durlauf (2005)]. Although, this approach is rather simple and intuitive, it is surprisingly under-utilized in the literature.

There are two more potential threats to identification. The first one is the possibility of sorting into reference groups based on unobserved factors [Manski (1993)]. More specifically, if there exist group-level unobserved factors that determine individual-level job satisfaction and are also correlated with the group-level job satisfaction, then the resulting estimates would be biased. Our empirical approach also allows us to address this problem by introducing group-level unobservables into the main estimating equation in a natural way. We control for sorting on unobservables in both the WERS and BHPS regressions. And, second, it is well-documented in the literature that the relative income structure within the reference group is an important determinant of the job satisfaction level in the peer group [Card et al. (2012)].

We also control for the pay-comparison effects in our calculations.

We find that one standard deviation increase in aggregate job satisfaction level leads to a 0.42 standard deviation increase in individual-level job satisfaction score at the workplace level and a 0.15 standard deviation increase in individual-level job satisfaction score at the local labor market level. In other words, we report that statistically significant job satisfaction spillovers exist both at the establishment level and local labor market level; and, the estimated spillovers are approximately three times larger at the establishment level than those at the local labor market level. These estimates can be restated in terms of the social multiplier: the corresponding social multipliers are [$1/(1 - 0.42) \approx$] 1.72 and [$1/(1 - 0.15) \approx$] 1.18 at the workplace and local labor market levels, respectively.[8] Back-of-the-envelope calculations yield the result that the Boeckerman and Ilmakunnas (2012) estimates—which say that one standard deviation increase in job satisfaction within the plant increases productivity per hours worked by 6.6 percent—would be revised up to 11.4 percent at the workplace level and 7.8 percent at the local labor market level after accounting for the job satisfaction spillovers. To summarize, these results suggest that (1) failing to account for the spillover externalities in job satisfaction may lead us to mis-assess the effectiveness of job satisfaction policies; thus, the policy maker should internalize these externalities, and (2) job satisfaction spillovers are much stronger at the workplace level than local labor market level; therefore, designing/enforcing job satisfaction policies at the workplace level will likely be more effective than implementing such policies at the local labor market level.

We also report estimates for contextual social effects. At the workplace level, we find that individual-level job satisfaction goes up with the fraction of male and older workers in the workplace. At the local labor market level, however, gender and age do not have any statistically significant contextual effect; instead, we only find that individual-level job satisfaction score goes down as the fraction of workers with greater access to promotion opportunities goes up in each industry $\times$ region cell. We also document that there are significant "income comparison effects" at the workplace, but not at the local labor market. In particular, we

[8] See Glaeser et al. (2003) for an excellent discussion of the social multiplier concept.

find that individual-level job satisfaction goes down with (*i*) average earnings and (*ii*) fraction of high earners—i.e., those who earn above the median wage within the relevant worker population—in the workplace. We discuss these results further in Section 4.

Our paper can be placed into the literature investigating social interactions in labor markets. There is a large body of literature testing the existence of peer effects in various labor market outcomes including productivity, wages, absenteeism, and learning (or knowledge spillovers). The results are mixed. For example, using grocery scanner data from a large supermarket chain, Mas and Moretti (2009) perform a field experiment among low-wage earners to analyze if the individual-level effort is influenced by a permanent increase in the productivity of co-workers and find reasonably large peer effects. Falk and Ichino (2006) study the behavior of high school students performing a simple task in a laboratory experiment to understand if individual-level performances are directly affected by the existence of other individuals doing the same task and they also document moderate peer effects. Ichino and Maggi (2000) find that group-level peer absenteeism increases individual absenteeism. In a field study, Bandiera et al. (2009) find that individual-level productivity responds to the skill-level of a friend working nearby, but does not respond to the skill-level of a non-friend working around. Guryan et al. (2009), on the other hand, find employing a random assignment exercise on a golf tournament data that individual-level performance is not influenced by the playing partners' ability. Cornelissen et al. (2013) report only small peer effects in wages among co-workers. While Azoulay et al. (2010) and Jackson and Bruegmann (2009) document significant knowledge spillovers among co-workers, Waldinger (2012) shows that those spillovers are weak, if they ever exist.

There are also several papers investigating contagion effects in subjective well-being measures. Using Chinese rural survey data, Knight and Gunatilaka (2009) examine whether happiness is infectious or not at the village level. Their results show that happiness is infectious in narrowly-defined reference groups. They exploit the panel feature of their dataset to account for the reflection problem and identify the relevant social effects. Papers in the psychology literature also find that happiness might be contagious in small environments.[9] However, these studies do not address the reflection problem, which might bias the results. Tumen and Zeydanli (2013), on the other hand, find that these contagion effects might disappear in more generally defined reference groups.

Our paper differs from this body of work and contributes to the related literature in three ways. First, this is the first paper in the literature estimating spillover effects in job satisfaction. We show that there exist statistically and economically significant job satisfaction spillovers in various work environments. Second, we show that the degree of these spillover externalities may change at different aggregation levels. Using two different datasets from the United Kingdom, we construct our reference groups at two aggregation levels: workplace level and local labor market level. The former defines peer effects in narrowly defined work settings, while the latter defines the social environment in larger ecological settings that embed more general aspects of community and working life. We document that the job satisfaction spillovers exist in both environments; but, they are much stronger at the workplace level than local labor market level. We further argue that this may have important policy implications. And, third, motivated by the hierarchical models of social processes, we develop an original identification strategy to separate endogenous effects from the contextual effects, controlling for group-level unobserved heterogeneity.

The plan of the paper is as follows. Section 2 provides an overview of the datasets we use and justifies the construction of our reference groups in different work settings. Section 3 explains the details of the econometric model and the identification strategy we employ. Section 4 presents the estimates, discusses in detail the results summarized above, and elaborates on the policy implications. Section 5 concludes.

2 Data and Reference Groups

In this section, we provide a detailed description of the two datasets we use in our empirical analysis: Workplace Employment Relations Survey and British Household Panel Survey. Both

[9] See, e.g., Hatfield et al. (1994), Sato and Yoshikawa (2007), and Fowler and Christakis (2008).

of these surveys are nationally representative datasets for the United Kingdom and provide establishment-level and individual-level labor market information, respectively. We also describe in detail the construction of our reference groups for both of these datasets. We focus on the 2004 editions of both datasets.

2.1 Workplace Employment Relations Survey (WERS)

WERS is a national survey of British employees constructed for the purpose of collecting information on employment relations in Britain.[10] The survey provides information about workers, working conditions, and industrial relations from all sectors except primary industries and private households with domestic staff. WERS 2004—the version that we use in our analysis—is the fifth among a series of surveys. Previous surveys are conducted in 1980, 1984, 1990, and 1998. In the 2004 cross-section, there are around 2,300 workplaces, 1,000 employee representatives, and 22,500 employees.

Consistent with the current practices in the literature, we construct the overall job satisfaction scores using the following seven question in the WERS-2004 dataset. How satisfied are you with

1) the sense of achievement you get from work?

2) the scope for using your own initiative?

3) the amount of influence you have over the job?

4) the training you receive?

5) the amount of pay you receive?

6) the job security?

7) the work itself?

The responses are based on a five-point scale with 1 representing "very satisfied," 2 "satisfied," 3 "neither satisfied nor dissatisfied," 4 "dissatisfied," and 5 "very dissatisfied." For each of the

[10] The most recent version of this dataset has been co-sponsored by the Department for Business, Innovation and Skills (BIS), Acas, the Economic and Social Research Council (ESRC), the UK Commission for Employment and Skills (UKCES), and the National Institute of Economic and Social Research (NIESR).

seven questions listed above, we construct a binary variable for the positive responses—taking the value 1 for the "very satisfied" or "satisfied" responses and 0 otherwise—and, then, we construct a sum of the seven binary variables for each individual to form an index with values from 0 to 7 [see also Jones et al. (2009), Jones and Sloane (2010), and Mumford and Smith (2013)].[11] We call this variable the "overall job satisfaction" score. The average overall job satisfaction score in our sample is 4.20 and the standard deviation is 2.13. The BHPS dataset, which we describe in the following subsection, has a 1–7 scale constructed based on different principles. For the sake of comparability of the estimates, we standardize the main job satisfaction measures in both WERS and BHPS around zero mean and unit variance. Thus, the dependent variable in our analysis will be the "standardized overall job satisfaction."

We control for a large set of individual- and job-related characteristics. To achieve consistency between the two datasets, we construct the WERS variables similar to their counterparts in the BHPS dataset. After excluding missing information on our control variables and dropping workplaces with less than two employees, the WERS dataset includes 1,673 workplaces/establishments and, in each workplace, up to 25 randomly-chosen employees taking the questionnaire. We start with describing the education variables. Since this is a workplace-level dataset, "No Qualification" category includes only a very small number of observations; thus, we drop the observations in this category and concentrate on the following education levels: "Higher Degree" (refers to postgraduate education), "First Degree" (refers to college education), "A-level," "O-level" (both referring to different classes of high-school education), and "Vocational Qualification." Earnings variable in the WERS is reported in 14 pre-specified intervals,[12] and, following Mumford and Smith (2009), we use the midpoints of these intervals as our earnings variable for each individual. In our sample, the average hourly log earnings is around 5.7. We also include relative earnings as a dummy variable taking 1 if the employee earns more than the median earnings in the sample. We categorize the job status under three sector categories: private sector job, public sector job, and other. An establishment size

[11] Although Mumford and Smith (2013) use the six facets of job satisfaction in the WERS, neglecting the training, Jones and Sloane (2010) use all of them. Jones et al. (2009) argue that training is also an important component for job satisfaction. We also include training.

[12] The question of the earnings variable is the following: "How much do you get paid for your job here, before tax and other deductions?"

variable is generated from the question of "Currently, how many employees do you have on the payroll at this establishment?" The answer varies from 5 to 10,000. We construct three variables for establishment size; small establishment (less than 50 employees), medium-size establishment (between 50 and 200 employees), and large establishment (more than 200 employees). Working hours are simply represented as a dummy variable taking 1 if the actual hours worked is above the sample mean and 0 otherwise.

Among approximately 20,035 employees and 1,673 establishments in our sample, the average age is 42, 47 percent are male, and 68 percent are married. Higher degree has the lowest fraction, whereas vocational qualifications have the highest. 46 percent of the employees are union members. 55 percent of the workplaces are publicly owned. Regarding the establishment size, the shares of small, medium, and large establishments are 0.32, 0.32, and 0.36, respectively. See Table (1) for detailed summary statistics for our WERS sample.

2.2 British Household Panel Survey (BHPS)

The BHPS provides information on individual-, household-, and job/employer-related characteristics from 1991 to 2008 in England, Scotland, Wales, and Northern Ireland. It yearly follows the same representative sample of households interviewing every adult member of sampled households. Eighteen waves of data are available. To make the two datasets comparable and compatible, we focus on the 2004 cross-section of the BHPS.

The individual-level job satisfaction in the BHPS dataset is reported based on a seven-point scale ranging from 1 (not satisfied at all) to 7 (completely satisfied). The employed workers are asked to rate the job satisfaction levels regarding the promotion prospects, total income, relationship with boss, job security, able to use their initiatives in the work, the actual work itself, and hours worked. The last question about job satisfaction is "Overall, how satisfied or dissatisfied are you with your present job?", which is again measured on the 1–7 scale and named the "overall job satisfaction." As we explain above, we standardize the overall job satisfaction score around zero mean and unit variance to achieve consistency across the job satisfaction measures we use for the WERS and BHPS datasets.

For the individual-level observed characteristics, we control for gender, age, education level, marital status, earnings, and pay comparisons. We collapse the education-levels into seven broad groups as follows: *higher degree* refers to postgraduate education, *first degree* refers to college education, *A-level*, *O-level*, and *other higher qualification* refer to high school graduates of different types (consistent with the education system in the UK), *vocational qualification* refers to teaching, nursing, commercial, apprenticeship, and the certificate of secondary education (CSE), and, finally, the ones with *no qualification*. The earnings variable—usual gross pay per month: current job—is recorded as the actual amount received and, thus, we simply take the natural logarithm of this variable in our analysis. We also consider the "taste for working hours" variable. Promotion opportunities is described by the binary variable taking 1 if the worker has access to promotion opportunities and 0 otherwise. The rest of the variables—firm size, job status, relative earnings, and union membership—are constructed similar to their counterparts in our WERS sample.

Table (2) presents the summary statistics of the sample that we use in our analysis. In order to be included into our sample, the respondent have to be employed and report an overall job satisfaction score. The mean age of the respondents is 40.4. Among the 6,428 observations, 47.4 percent are male, 57.3 percent are married, 4.4 percent have higher degree, 15.8 percent have first degree, another 12.6 percent have A-level degree, 17.6 percent have O-level degree, 30.8 percent have other higher qualifications, 9.4 percent have vocational qualifications, and the remaining 9.4 percent have no qualifications. Before standardization, the mean overall job satisfaction score is approximately 5.4 out of 7, with a standard deviation of 1.26. 79 percent are employed in full-time jobs. 63 percent are employed in privately-owned firms. 32.8 percent prefer to work fewer hours. 48.6 percent are employed in small-size firms. See Table (2) for further information on region- and industry-specific details. We generate group-level variables based on our reference groups constructed as industry $\times$ region cells. Below we describe how we construct our reference groups both in the WERS and BHPS datasets.

2.3 Reference Groups

Our primary objective is to separately identify endogenous social effects and contextual social effects in job satisfaction within a formal empirical model of social interactions. We conceptualize the social interactions that we estimate as the existence of "spillovers" in the society in the sense that the group-level job satisfaction in one's reference group affects the individual worker's perception of own job satisfaction. We perform this task at two levels with two different datasets from the United Kingdom. First, we use the WERS dataset to estimate spillovers at the workplace level. And, second, we use the BHPS dataset to estimate job satisfaction spillovers at the local labor market level. The WERS dataset captures the social effects among co-workers, who are directly interacting. The BHPS dataset, on the other hand, captures social effects among individuals who are potentially interacting indirectly. As Bramoulle et al. (2009) clearly state, this type of social effects is based on the idea that "neighbors in the neighborhood do not affect me directly; what matters is the neighborhood itself."

WERS. The WERS datasets naturally offers establishment-level reference groups; that is, all workers employed in a given establishment constitute the reference group for each of the workers employed in that establishment. There are 1,673 establishments in our WERS sample. Thus, the number of reference groups is 1,673. The average group size is approximately 12 worker per establishment. This setting defines narrow reference groups hypothesizing that social forces operate at the workplace level: workers in a given establishment are exposed to similar work-specific conditions that shape their job satisfaction perceptions. The group-level counterparts of the individual-level variables are constructed taking averages at the workplace level. Similarly, the endogenous social variable (the group-level job satisfaction score) is calculated by averaging the job satisfaction scores within the workplace.

BHPS. For the BHPS dataset, we construct industry $\times$ region cells as our reference groups. In terms of our conceptualization of social interactions, this means that we try to capture the social forces that operate among workers who are geographically close to each other and who are potentially exposed to similar local labor market conditions specific to the industries they belong to. This is a common way of constructing reference groups in the empirical social interactions studies, particularly the ones handling large datasets. For example, Luttmer (2005) utilizes the outgoing rotation groups feature of the Current Population Survey and constructs industry × occupation cells to estimate the neighborhood effects of income on individual-level happiness. Similarly, Ferrer-i-Carbonell (2005) uses the German Socio-Economic Panel and constructs education × age × region cells to estimate the impact of the group-level income on individual-level subjective well-being. In a similar context, Glaeser et al. (1996) construct region-specific cells on a lattice to estimate the impact of neighbors' criminal-activity decisions on the agent's own decision to participate in crime. In another example, Stutzer and Lalive (2004) use data from Switzerland cantons and construct canton-level cells to estimate the effect of social norm to work—roughly, the rate of employment in one's neighborhood—on how quickly the unemployed individual finds a job, probably due to social pressure. The examples can be extended further. In all of these papers, large reference groups are constructed to capture the peer influences in broad social settings.

In our BHPS sample, the following twelve regions describe the geographical clustering: 1) London, 2) South East, 3) South West, 4) East Anglia, 5) East Midlands, 6) West Midlands, 7) North West, 8) North East, 9) Yorkshire & Humberside, 10) Wales, 11) Scotland, and 12) Northern Ireland [see Figure]. Nine industry categories are selected at one-digit level as follows: 1) energy & water supplies, 2) extraction of minerals & manufacture of metal goods, mineral products & chemicals, 3) metal goods, engineering & vehicles, 4) other manufacturing industries, 5) construction, 6) distribution, hotels & catering (repairs), 7) transport & communication, 8) banking, finance, insurance, business services & leasing, and 9) other services. At the end, there are 108 reference groups in our BHPS sample. The average group size is approximately 60 workers per industry × region cell.

3 Econometric Framework

The econometric framework that we employ in this paper is a version of the canonical linear-in-means model of social interactions. Our ultimate goal is to estimate social interactions in job satisfaction. In particular, we would like to estimate the effects of (1) group-level job satisfaction—the "endogenous social effect"—and (2) group-level exogenous characteristics—the "contextual effects"—on individual-level job satisfaction, controlling for unobserved group-level heterogeneity. The linear-in-means model of social interactions is plagued with the well-known "reflection problem," which masks the econometric identification of social interactions [Manski (1993)]. The simplest way to resolve this issue is to use an appropriately formulated instrumental variables strategy. When an instrument is not available, it is necessary to invoke nonlinearities to identify social interactions [Brock and Durlauf (2001a), Blume et al. (2011)].

In this paper, we use an empirical strategy that allows us to convert the standard linear model into a nonlinear one. The motivation comes from the hierarchical models of social processes. This hierarchical structure secures identification of social interactions via introducing cross-product terms into the standard model. This section provides a detailed description of our econometric model for the purpose of familiarizing the reader with the basic concepts we frequently mention throughout the paper. Section 3.1 presents our empirical model and the associated technical issues (i.e., the reflection problem) including a formal statement of the conditions required to identify social interactions. Section 3.2 describes our hierarchical model and assesses in detail how we achieve identification.

3.1 The Empirical Model of Social Interactions

Each individual $i \in \mathcal{I}$ is a member of a group $g \in \mathcal{G}$, where $\mathcal{I}$ is the number of individuals in the worker population and $\mathcal{G}$ is the number of groups, with $\mathcal{I} > \mathcal{G}$. The following linear-in-means equation is an empirical tool commonly used in the literature:

$$\omega_{i_g} = \beta_0 + \beta_1 \boldsymbol{X}_{i_g} + \beta_2 \boldsymbol{Y}_g + J m_g + u_g + \epsilon_{i_g}, \tag{3.1}$$

where the dependent variable, ω_{i_g}, is the individual-level job satisfaction for person i in group g, $\boldsymbol{X}_{i_g}$ is a vector of individual-level observed characteristics of i in group g, $\boldsymbol{Y}_g$ is a vector of group-level observed characteristics of group g, $m_g = \mathbb{E}[\omega_{i_g} | g, F_{i_g}]$ is the mean job satisfaction in group g, u_g is a group-level unobserved factor common across the members of group g, and ϵ_{i_g} is a random error term with $\mathbb{E}[\epsilon_{i_g}|g, F_{i_g}] = 0$. In our notation, F_{i_g} corresponds to the empirical distribution of individuals in group g and this distribution is possibly different for each group. The distinction between β_2 (contextual effects) and J (endogenous effect) is the key notion in this model. The former measures the effect of exogenous group-level variables on the individual-level outcome, while the latter measures the effect of endogenous group-level outcome on the individual-level outcome. Our ultimate goal is to clearly distinguish β_2 from J and to separately identify the effects of group-level variables on the individual-level outcome. However, econometric identification is a problematic issue in this standard setting. In what follows, we shut down the group-level unobserved effect u_g for notational simplicity. It will reappear in our final equation.

To define the identification problem, we take the conditional mathematical expectations of both sides of the linear-in-means equation, where the conditioning is on g and F_{i_g}, for all i and g. This gives us

$$m_g = \beta_0 + \beta_1 \boldsymbol{X}_g + \beta_2 \boldsymbol{Y}_g + J m_g, \tag{3.2}$$

where $\boldsymbol{X}_g = \mathbb{E}[\boldsymbol{X}_{i_g}|g, F_{i_g}]$. $\boldsymbol{X}_g$ can be named as the group-level mean of individual-level observed characteristics and it may or may not coincide with $\boldsymbol{Y}_g$. Notice that m_g appears in both sides of Equation (3.2). Solving for m_g yields the result that

$$m_g = \frac{\beta_0}{1-J} + \frac{\beta_1}{1-J}\boldsymbol{X}_g + \frac{\beta_2}{1-J}\boldsymbol{Y}_g. \tag{3.3}$$

The reflection problem states that if the dimensions of the vectors $\boldsymbol{X}_g$ and $\boldsymbol{Y}_g$ are the same, then linearity masks the econometric identification of the (endogenous) social interactions parameter J.

To formalize this statement, we plug Equation (3.3) into Equation (3.1), which gives us the estimating equation

$$\omega_{i_g} = \frac{\beta_0}{1-J} + \beta_1 \boldsymbol{X}_{i_g} + \frac{J\beta_1}{1-J}\boldsymbol{X}_g + \frac{\beta_2}{1-J}\boldsymbol{Y}_g + \epsilon_{i_g}. \tag{3.4}$$

When the reflection problem is in effect, J and β_2 cannot be distinguished from each other, which implies that social interactions cannot be identified. To see this, set $\boldsymbol{X}_g = \boldsymbol{Y}_g$, which yields the equation

$$\omega_{i_g} = \frac{\beta_0}{1-J} + \beta_1 \boldsymbol{X}_{i_g} + \frac{J\beta_1 + \beta_2}{1-J}\boldsymbol{Y}_g + \epsilon_{i_g}. \tag{3.5}$$

It is obvious that, in this equation, it is impossible to separate J from β_2 econometrically.

One solution is the existence of an additional X_g which is not in $\boldsymbol{Y}_g$. If such an X_g exists, then endogenous social interactions (J)—and also all the other model parameters—are identified by applying simple ordinary least-squares method on Equation (3.4). In other words, one individual-level variable, the mean of which cannot be regarded as a group-level variable, is required for identification of social interactions.

To demonstrate this, let $\tilde{X}_g$ be an element of the set $\boldsymbol{X}_g$ and let $\tilde{\beta}_1$ be the coefficient associated with $\tilde{X}_g$. Let $\tilde{X}_g \notin \boldsymbol{Y}_g$. Then, Equation (3.4) can be rewritten as

$$\omega_{i_g} = \frac{\beta_0}{1-J} + \bar{\beta}_1 \boldsymbol{X}_{i_g} + \frac{J\tilde{\beta}_1}{1-J}\tilde{X}_g + \frac{\beta_2}{1-J}\boldsymbol{Y}_g + \epsilon_{i_g}, \tag{3.6}$$

where $\bar{\beta}_1$ describes the elements of the parameter vector β_1 excluding $\tilde{\beta}_1$ (i.e., $\bar{\beta}_1$ and $\tilde{\beta}_1$ jointly constitute β_1). From Equation (3.6), $\tilde{\beta}_1$ can be identified, which implies that J and β_2 can separately be identified within this framework. The key point is the existence of a variable $\tilde{X}_g$, which does not correspond to a contextual effect $\boldsymbol{Y}_g$. Individual-level variables such as gender, education, age, marital status, and so on necessarily correspond to contextual effects when averaged out. One should find an individual-level variable $\tilde{X}_g$ such that it cannot be interpreted as a group-level characteristic. If such a variable exists, it serves as an instrumental variable (IV) and secures identification of J and β_2 separately. Unfortunately, most of the large datasets—such as BHPS, GSOEP, WERS, etc.—do not include a variable $\tilde{X}_g$ that can naturally fit into the IV definition provided above.

One popular alternative to IV is to introduce nonlinearities into the linear-in-means specification. To demonstrate how nonlinearities secure identification, we modify the standard model as follows:

$$\omega_{i_g} = \beta_0 + \beta_1 \boldsymbol{X}_{i_g} + \beta_2 \boldsymbol{Y}_g + J\phi(m_g) + \epsilon_{i_g}, \tag{3.7}$$

where $\phi(\cdot)$ has non-zero second derivatives; that is, it is a legitimate nonlinear function. Without loss of generality, we assume also that $\phi(\cdot)$ is invertible. Again, taking the conditional mathematical expectations of both sides and rearranging the terms in such a way that the terms with m_g appears on the left and the rest of the variables on the right, we get the equation

$$\Phi(m_g) = \beta_0 + \beta_1 \boldsymbol{X}_g + \beta_2 \boldsymbol{Y}_g, \tag{3.8}$$

where $\Phi(m_g) = m_g - J\phi(m_g)$. The functions $\phi(\cdot)$ and $\Phi(\cdot)$ has the same properties, therefore we can invert $\Phi(\cdot)$ to get

$$m_g = \Phi^{-1}\left(\beta_0 + \beta_1 \boldsymbol{X}_g + \beta_2 \boldsymbol{Y}_g\right) \tag{3.9}$$

and plugging this into the original estimating equation we get

$$\omega_{i_g} = \beta_0 + \beta_1 \boldsymbol{X}_{i_g} + \beta_2 \boldsymbol{Y}_g + J\phi\left[\Phi^{-1}\left(\beta_0 + \beta_1 \boldsymbol{X}_g + \beta_2 \boldsymbol{Y}_g\right)\right] + \epsilon_{i_g}. \tag{3.10}$$

In such a setting, we can identify β_2 and J separately without a further need for an exclusion restriction (or an IV); that is, we do not need the condition that $\dim(\boldsymbol{X}_g) = \dim(\boldsymbol{Y}_g) + 1$, where dim denotes the dimension of the corresponding vector.

One problem with this framework is that there is no systematic way to choose the functional form of $\phi(\cdot)$. In this paper, we propose an estimation strategy that introduces a systematic way to embed nonlinearities into the standard empirical specification. To be specific, we construct a hierarchical model which has the additional advantage of being consistent with our definition and conceptualization of social interactions in job satisfaction. The next section presents the details.

3.2 The Hierarchical Model

Suppose that the Equation (3.1) is modified as follows:

$$\omega_{i_g} = \alpha_0\left(\boldsymbol{Y}_g\right) + \alpha_1\left(\boldsymbol{Y}_g\right)\boldsymbol{X}_{i_g} + \alpha_J\left(\boldsymbol{Y}_g\right)m_g + u_g + \epsilon_{i_g}. \tag{3.11}$$

In words, the coefficients α_0, α_1, and α_J are stated as functions of the contextual variables, $\boldsymbol{Y}_g$, which define the "social context." In other words, the contextual variables describe the properties of the environments that the individuals live in. Setting up the regression coefficients in this way implies that social groups describe ecologies in which decisions are made and matter because different ecologies induce different mappings from the individual determinants of these behaviors and choices. To convert this setting into an empirical equation that we can estimate, we make the following simplifying assumptions:

$$\begin{aligned}
\alpha_0\left(\boldsymbol{Y}_g\right) &= \beta_0 + \beta_2\boldsymbol{Y}_g, \\
\alpha_1\left(\boldsymbol{Y}_g\right) &= \beta_1 + \boldsymbol{bY_g}, \\
\alpha_J\left(\boldsymbol{Y}_g\right) &= J + \pi\boldsymbol{Y_g}.
\end{aligned}$$

Plugging these expressions into Equation (3.11) yields

$$\omega_{i_g} = \beta_0 + \beta_1\boldsymbol{X}_{i_g} + \beta_2\boldsymbol{Y}_g + Jm_g + \pi\boldsymbol{Y_g}m_g + \boldsymbol{Y}_g'\boldsymbol{B}\boldsymbol{X}_{i_g} + u_g + \epsilon_{i_g}, \tag{3.12}$$

where $\boldsymbol{B}$ is the matrix form of the coefficient vector $\boldsymbol{b}$. This equation looks very similar to our original linear-in-means specification except that we include interaction terms in the form of cross products motivated by the hierarchical model.

Note that the structure of the data at hand forces us to specify the unobserved group-level effect u_g as a random term. The reason is that the WERS dataset surveys up to 25 workers in each establishment; that is, the group-level effects will be based on a sample of workers in each group, rather than full population. In such a situation, the true unobserved group-level effect can be controlled for up to a random error. A common way to resolve this issue is to assume that u_g is itself random rather than fixed. Accordingly, we assume that the unobserved group-level factors that might lead to the sorting problem in the form of common influences on individual-level job satisfaction is a random term with zero mean and non-zero variance. We also cluster standard errors at the group level, which means that we account for within-group correlations in the error structure.

To demonstrate how this formulation secures identification, we take the conditional mathematical expectations of both sides, as before, and solve the resulting equation for m_g, which gives us

$$m_g = \frac{\beta_0 + \beta_1 \boldsymbol{X}_g + \beta_2 \boldsymbol{Y}_g + \boldsymbol{Y}_g' \boldsymbol{B} \boldsymbol{X}_g}{1 - J - \pi \boldsymbol{Y}_g}. \tag{3.13}$$

Notice that, very similar to the motivation behind the nonlinear model, this model also introduces non-linearity between m_g and the other regressors, when we impose $\boldsymbol{X}_g = \boldsymbol{Y}_g$. There is no need for an exclusion restriction and econometric identification of social influences is immediate given standard conditions on individual- and group-level observed covariates [see Blume and Durlauf (2005) for further details]. This formulation is consistent with our hypothesis and our definition of social interactions.

At the end, we estimate Equation (3.12) to separately identify β_2 and J. In this setup, the endogenous social effect is $J + \pi \bar{\boldsymbol{Y}}_{\boldsymbol{g}}$, where $\bar{\boldsymbol{Y}}_{\boldsymbol{g}}$ are the sample means of group-level variables, i.e., the endogenous effect is no more J since we have cross-product terms in the regressions. The same logic applies to the contextual effects we estimate. The estimates we report and discuss in Section 4 directly refer to these "marginal effects."

4 Results and Discussion

We estimate Equation (3.12) using two datasets: WERS and BHPS. In WERS, establishments are the reference groups, whereas, in BHPS, reference groups are defined by the industry ×

region cells. We group our estimates under three categories: individual-level coefficients, endogenous social effects, and contextual social effects. Individual-level coefficients describe the impact of individual-level observed covariates on the job satisfaction score. The endogenous social effect refers to the effect of the mean job satisfaction—where the mean is calculated at the group level—on the job satisfaction score. The contextual social effect refers to the effect of group-level counterparts of the individual-level covariates on the job satisfaction score. Below we discuss our estimates in detail. Note that we report "marginal effects," which means that our estimates are readily interpretable in terms of our parameters of interest. Note also that both the individual- and group-level job satisfaction scores are standardized around mean zero and unit variance.

4.1 Estimates for the Individual-level Coefficients

Our estimates for the individual-level coefficients are parallel to those reported in the previous empirical literature on the determinants of job satisfaction [see, for example, Clark (1996), Clark and Oswald (1996), and Taylor (2006)]. Specifically, for both WERS and BHPS, we find that females, married workers, younger workers, workers with higher earnings, workers earning more than the median wage earner in the population, workers with greater access to promotion opportunities, and workers employed in smaller establishments are more satisfied jobwise.[13] Tables (3) and (5) report the estimates of individual-level covariates for the WERS and BHPS datasets, respectively. This paper focuses on estimating spillovers in job satisfaction; thus, the rest of the paper aims to interpret the estimated social effects rather than providing a lengthy discussion of the individual-level covariates.

4.2 Estimates for Endogenous Social Interactions

A group-level variable is endogenous if its individual-level counterpart is the choice variable of interest. Hence, the associated group-level variable can be defined as the effect of other people's behavior on individual-level behavior. This a classic example of spillover externalities. The findings from our benchmark estimates verify that there exist significant positive

[13]Note that the estimates for the promotion opportunities are only relevant for the BHPS, since the WERS dataset does not include a question regarding the promotion prospects of the employees.

spillover externalities in job satisfaction; that is, the group-level (i.e., mean) job satisfaction is positively related to individual-level job satisfaction. To put it differently, an individual worker's job satisfaction level tend to be higher in a group of workers who are highly satisfied jobwise. We document these effects for both the WERS and BHPS samples. We find that one standard deviation increase in aggregate job satisfaction level leads to a 0.42 standard deviation increase in individual-level job satisfaction at the workplace level and 0.15 standard deviation increase in individual-level job satisfaction at the local labor market level. Tables (4) and (6) report the estimates of endogenous spillovers for the WERS and BHPS datasets, respectively. Job satisfaction is often associated with workplace attitudes such as involvement in the organization, relatedness with co-workers/customers/managers, attachment, motivation, shirking, tendency to slow down work, absenteeism, etc. These attitudes form a workplace "atmosphere" and jointly contribute to the formation of worker satisfaction and performance. Our estimates confirm that the aggregate job satisfaction level in a certain work environment can be regarded as a "social" variable and may, in turn, affect individual-level job satisfaction significantly.

This result suggests that there are huge gains to policy interventions to increase individual-level job satisfaction as there are large positive feedback effects from group-level job satisfaction toward individual-level job satisfaction in the form of spillover externalities.[14] The degree of this feedback is larger at the workplace level than local labor market level. Thus, enforcing job satisfaction policies at the workplace level will likely be more effective than implementing such policies at the local labor market level. This result is particularly important, because it is reported in the literature that job satisfaction is positively related to worker productivity [see, for example, Boeckerman and Ilmakunnas (2012)]. In terms of the magnitudes, Boeckerman and Ilmakunnas (2012) report that one standard deviation increase in group-level job satisfaction raises productivity per hours worked by 6.6 percent. This means that the existence of spillover externalities introduces notable gains to increasing job satisfaction at the individual level.

[14]Employers can stimulate social interactions among workers, which suggests that the optimal design of worker groups/teams should also account for these social forces [Tumen (2012)].

4.3 Estimates for the Contextual Effects

We control for a large set of contextual variables in our regressions. However, only a few of them produce statistically significant coefficients. We start with the WERS results, in which we report estimates for social interactions at the workplace level. Our WERS regressions [see Table (4)] show that the Male, Age, Log Earnings, and Relative Earnings variables are subject to statistically significant contextual social effects. To begin with, we show that working close to a group of workers with a larger fraction of males increases job satisfaction at the workplace-level analysis. This result can be interpreted in several ways. It is well-documented in the literature that females are more likely to be absent from work due to illness-related reasons.[15] If this is the case, workplace attitudes such as motivation, attachment, and involvement might be weaker for females than males due to these relatively more frequent breaks in their work attendance. As a consequence, working in a group with a greater fraction of males might increase motivation and, thus, job satisfaction. A second explanation might be related to gender discrimination; that is, our finding can be interpreted as the existence of distaste against women. However, we are cautious on this interpretation as we do not have additional empirical support for this claim in our analysis. Apart from the contextual gender effects, we document that job satisfaction is higher in groups with higher average worker age and this positive impact becomes weaker as the average age goes up in our WERS sample. This can be attributed—using the Mincerian language—to labor market experience. Working in a group with a larger fraction of experienced workers may produce external effects boosting job satisfaction and, thus, worker productivity.

We also find that earnings have statistically significant contextual effects in our WERS regressions. The contextual earnings effect refers to the effect of the mean earnings in one's reference group on individual-level job satisfaction. To comply with the conventions in the literature, we construct two earnings variables: (1) the natural logarithm of earnings and (2) a dummy variable indicating the earnings rank of the worker, i.e., relative earnings. As we report in Table (4)], the average earnings in the reference group is negatively related to the individual

[15] Ichino and Moretti (2009) show that this may be related to menstrual cycles.

job satisfaction score. Moreover, working in a group with a greater fraction workers earning more than the median wage also reduces individual job satisfaction.[16] This is consistent with the findings in the pay-comparisons literature, which suggest that job satisfaction depends on relative income comparisons [see, for example, Clark et al. (2009) and Card et al. (2012)]. Our findings confirm the view that income is evaluated relative to some comparison level based on the reference group and not only in absolute terms. This is in line with the findings reported in the literature [see, e.g., Easterlin (1973)].

For the BHPS analysis, we do not find any statistically significant contextual effects for the Male, Age, Log Earnings, and Relative Earnings variables at the local labor market level, unlike our workplace level analysis. This may be due to the reason that individuals care less about the group-level exogenous characteristics in larger reference groups. However, we do report a different contextual effect at the local labor market level: the promotion opportunities, a variable that does not exist in the WERS dataset. Specifically, we find that working in groups with a greater fraction of workers with access to promotion opportunities reduces individual-level job satisfaction [see Table (6)]. This can be attributed to competition: that is, if there is a large fraction of workers in one's reference group expecting promotions, then this might increase excess competition in the work environment and, therefore, might reduce job satisfaction. It is interesting, however, detecting this result at the local labor market level. This may be suggesting that working in industries with harsher competition conditions reduces individual-level job satisfaction. We do not have results for this variable at the workplace level; however, if the competition hypothesis is true, we conjecture that the contextual effect of promotion opportunities would be even stronger at the workplace level.

5 Concluding Remarks

There is a large literature arguing that peer effects exist in various labor market outcomes including productivity, wages, absenteeism, and learning (or knowledge spillovers). We contribute to this literature in three ways. First, this is the first paper in the literature testing the

[16] So, instead of the Hirschman's tunnel effect, we observe that envy/hatred is more likely to be effective.

existence of job satisfaction spillovers. We show that there exist significant positive spillovers in job satisfaction. Second, we perform our analysis at two different aggregation levels using two different datasets from the United Kingdom. We find that the job satisfaction spillovers are almost three times stronger at the workplace level than local labor market level (defined in terms of industry $\times$ region cells). This implies that although job satisfaction spillovers are strong among narrowly defined worker groups, it would be misleading to exclude the possibility of spillovers in broader reference groups. In other words, regional aspects of working life and conditions in the local labor markets may also induce interactions among people that can exhibit nonnegligible social effects. Finally, we make a methodological contribution to the empirical literature by resolving the identification problem using an intuitive insight from the hierarchical models of social processes. Specifically, we hypothesize that our parameters of interest are determined within the social environments they originate from. Under reasonable specifications, this logic implies introducing certain cross-product terms into the standard estimating equations.

We conclude that there are sizable social interactions in job satisfaction that should not be ignored in assessing policy effectiveness. The policy makers should internalize these spillover externalities. Our estimates also provide guidance on the question "at which level job satisfaction spillovers should be internalized." We argue that firms should design and implement their own job satisfaction policies rather than relying on more general policies or institutional regulations that could only be enforced at the local labor market level (or industry level).

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Variable	**Mean**	**Std.Dev**
Overall job satisfaction	4.20	2.11
Std. overall job satisfaction	1.07e-08	1
Individual-level Characteristics		
Male	0.469	0.499
Married	0.682	0.466
Age	41.646	12.095
Higher degree	0.009	0.092
First degree	0.033	0.18
'A'-level	0.273	0.446
'O'-level	0.238	0.426
Vocational qual.	0.446	0.497
Log earnings	5.692	0.74
Relative earnings	0.518	0.5
Working hours	0.656	0.475
Job-level Characteristics		
Private sector	0.365	0.481
Public sector	0.551	0.497
Union membership	0.462	0.499
Small-size establishment	0.324	0.468
Medium-size establishment	0.318	0.466
Large-size establishment	0.358	0.48
# of observations	20,035	
# of workplaces/establishments	1,673	

Table 1: Summary Statistics – WERS. Workplace Employment Relations Survey 2004 dataset is used to construct this table.

Variable	Mean	Std.Dev
Overall job satisfaction	5.40	1.26
Std. overall job satisfaction	-3.13e-09	1
Individual-level Characteristics		
Male	0.474	0.499
Married	0.573	0.495
Age	40.351	12.049
Higher degree	0.044	0.205
First degree	0.158	0.365
'A'-level	0.126	0.332
'O'-level	0.176	0.381
Other higher qual.	0.308	0.462
Vocational qual.	0.094	0.292
No qual.	0.094	0.291
Log earnings	6.907	0.707
Relative earnings	0.531	0.499
Job-level Characteristics		
Union membership	0.525	0.499
Promotion opportunities	0.499	0.5
Full-time job	0.79	0.407
Private sector	0.63	0.48
Public sector	0.22	0.42
Prefer to work fewer hours	0.328	0.47
Prefer to work more hours	0.054	0.226
Prefer to contain same hours	0.618	0.486
Small-size establishment	0.486	0.5
Medium-size establishment	0.216	0.411
Large-size establishment	0.299	0.458
Industries		
Energy-water supplies	0.036	0.186
Extraction-manufacture	0.074	0.262
Metal goods-engineering	0.046	0.21
Other manufacturing	0.058	0.235
Construction	0.178	0.383
Distribution, hotels, catering	0.096	0.295
Transport-communication	0.196	0.397
Banking-finance	0.254	0.435
Other services	0.061	0.239
Regions		
London	0.05	0.219
South East	0.114	0.318
South West	0.054	0.226
East Anglia	0.024	0.154
East Midlands	0.052	0.222
West Midlands	0.046	0.209
Northwest	0.066	0.249
Yorkshire-Humberside	0.054	0.226
North East	0.037	0.189
Wales	0.148	0.355
Scotland	0.188	0.391
Northern Ireland	0.166	0.372
# of observations	6,428	

Table 2: Summary Statistics – BHPS. British Household Panel Survey 2004 cross-section is used to construct this table.

Dependent variable: job satisfaction score (standardized)			
Marginal effects for individual-level variables			
Covariate	**Coefficient**	**(Standard Error)**	p**-value**
Male	-0.160***	(0.017)	0.000
Married	0.063***	(0.016)	0.000
Age	-0.031***	(0.005)	0.000
Age-squared/100	0.039***	(0.005)	0.000
First degree	0.147	(0.161)	0.359
‘A’-level	0.265*	(0.150)	0.077
‘O’-level	0.298**	(0.50)	0.046
Vocational qual.	0.430***	(0.149)	0.004
Log earnings	0.232***	(0.022)	0.000
Relative earnings	0.083***	(0.021)	0.000
Working hours	-0.076***	(0.020)	0.000
# of observations		20,035	

Table 3: Estimation results (WERS – individual-level coefficients). *, **, *** indicate the 10%, 5%, and 1% significance levels, respectively. Standard errors, clustered at the group level, are reported in parentheses. Group-level unobserved effects are controlled for.

Dependent variable: job satisfaction score (standardized)

Marginal effects for group-level variables

Covariate	Coefficient	(Standard Error)	p-value
Endogenous social effect			
Mean job satisfaction (standardized)	0.423***	(0.007)	0.000
Contextual effects: means of individual characteristics			
Male	0.157***	(0.038)	0.000
Married	-0.075	(0.051)	0.142
Age	0.026**	(0.013)	0.043
Age-squared/100	-0.034**	(0.015)	0.022
First degree	0.094	(0.341)	0.783
'A'-level	-0.073	(0.307)	0.812
'O'-level	-0.099	(0.305)	0.744
Vocational qual.	-0.211	(0.302)	0.484
Log earnings	-0.203***	(0.032)	0.000
Relative earnings	-0.093*	(0.057)	0.103
Working hours	0.047	(0.044)	0.283
Contextual effects: means of establishment/job characteristics			
Private sector	-0.003	(0.028)	0.906
Public sector	-0.004	(0.027)	0.885
Not union member	-0.015	(0.030)	0.613
Medium-size establishment	-0.003	(0.017)	0.841
Large establishment	-0.006	(0.017)	0.746
# of observations		20,035	

Table 4: ESTIMATION RESULTS (WERS – GROUP-LEVEL COEFFICIENTS). *, **, *** indicate the 10%, 5%, and 1% significance levels, respectively. Standard errors, clustered at the group level, are reported in parentheses. Group-level unobserved effects are controlled for.

Dependent variable: job satisfaction score (standardized)			
Marginal effects for individual-level variables			
Covariate	**Coefficient**	**(Standard Error)**	***p*-value**
Individual characteristics			
Male	-0.172***	(0.030)	0.000
Married	0.161***	(0.027)	0.000
Age	-0.028***	(0.007)	0.000
Age-squared/100	0.039***	(0.009)	0.000
Higher degree	0.262**	(0.102)	0.010
First degree	0.194**	(0.099)	0.049
'A'-level	0.142	(0.091)	0.120
'O'-level	0.235**	(0.094)	0.013
Other higher qual.	0.137	(0.096)	0.152
Vocational qual.	0.052	(0.094)	0.582
Log earnings	0.119***	(0.035)	0.001
Relative earnings	0.111***	(0.038)	0.003
Job characteristics			
Private sector	-0.025	(0.083)	0.762
Public sector	-0.127	(0.096)	0.186
Union membership	-0.060*	(0.033)	0.066
Promotion opportunities	0.282***	(0.026)	0.000
Full-time job	-0.183***	(0.044)	0.000
Prefer to work fewer hours	-0.393***	(0.027)	0.000
Medium-size establishment	-0.181***	(0.033)	0.000
Large establishment	-0.162***	(0.033)	0.000
# of observations		6,428	

Table 5: Estimation results (BHPS – individual-level coefficients). *, **, *** indicate the 10%, 5%, and 1% significance levels, respectively. Standard errors, clustered at the group level, are reported in parentheses. Group-level unobserved effects are controlled for.

Dependent variable: job satisfaction score (standardized)

Marginal effects for group-level variables

Covariate	**Coefficient**	**(Standard Error)**	**p-value**
Endogenous social effect			
Mean job satisfaction (standardized)	0.147***	(0.028)	0.000
Contextual effects: means of individual characteristics			
Male	0.328	(0.244)	0.178
Married	0.368	(0.303)	0.224
Age	0.094	(0.070)	0.178
Age-squared/100	-0.144*	(0.084)	0.086
Higher degree	-1.033	(0.771)	0.180
First degree	-1.048	(0.742)	0.158
'A'-level	-0.701	(0.602)	0.245
'O'-level	-0.889	(0.671)	0.185
Other higher qual.	-0.888	(0.788)	0.260
Vocational qual.	-1.152	(0.790)	0.145
Log earnings	-0.198	(0.193)	0.306
Relative earnings	-0.233	(0.423)	0.581
Contextual effects: means of job characteristics			
Private sector	0.196	(0.272)	0.943
Public sector	0.082	(0.287)	0.774
Union membership	0.178	(0.200)	0.372
Promotion opportunities	-0.430*	(0.236)	0.068
Full-time job	-0.244	(0.445)	0.584
Prefer to work fewer hours	0.276	(0.279)	0.322
Medium-size establishment	0.310	(0.337)	0.357
Large establishment	-0.052	(0.273)	0.850
# of observations		6,428	

Table 6: Estimation results (BHPS – group-level coefficients). *, **, *** indicate the 10%, 5%, and 1% significance levels, respectively. Standard errors, clustered at the group level, are reported in parentheses. Group-level unobserved effects are controlled for.