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Luck, Effort, and Reward in an Organizational Hierarchy

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Using the personnel records of a large British financial sector employer we investigate how workers respond to remuneration differences and "luck" in the promotion system. The results confirm that workers respond to larger remuneration spreads by working harder. Increased certainty in the promotion process also has this effect. There appears to be no difference between men's and women's reactions to promotion incentives. Gender differences in the raw data therefore appear not due to incentives. We need to look elsewhere for an explanation.

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I. Introduction

In this article, we investigate empirically the respective roles of incentives and good fortune in a hierarchical promotion system. The article is unusual in two respects: first, most of the literature that seeks to assess the impact of reward schemes on effort uses data from sports (see Prendergast 1999, pp. 34–36), whereas we use data from a contemporary industrial context. Second, we develop a method that allows us to extract information from our data about the promotion uncertainty in the system. This enables us to form a more complete view of the effort supply function than has previously been available and, in particular, to estimate the impact on effort of increased uncertainty in the promotion system.

Our main theoretical vehicle is the tournament model introduced by Lazear and Rosen (1981). Their model predicts that the supply of effort by workers in a promotion tournament will depend on two aspects of their contract: the reward received for promotion and the "luck" experienced by individual contenders for promotion. In addition, attitudes to risk and the shape of the effort cost function are important in fixing the shape of the effort supply function. The model and its implications have been the subject of much theoretical debate. A brief resume of the relevant theory is presented in Section II. Many of the issues and much of the theoretical debate surrounding the model are discussed by McLaughlin (1986); for a wider discussion of incentives in firms, see Prendergast (1999).

The three key variables—effort, reward, and luck—are measured using information from a large British financial firm. Our effort measure is derived from the absenteeism records of the firm. Rewards to promotion at various levels of the hierarchy are calculated from payroll data that include information on salary and bonuses. The influence of luck on promotion decisions for each individual is estimated using the past record of promotions in the firm. Section III below contains details of the data and discussions of each of the three key variables.

Section IV describes the dynamic binary choice model used to estimate the parameters of the model. The estimation incorporates a correction for possible bias resulting from the dependency of unobserved components on the regressors, and from a test for bias resulting from failure to account for the influence of initial conditions on the panel. Section V reports the results. These provide support for the idea that increased prize spreads have positive effects on effort and that increased certainty in the promotion process enhances these effects. Despite the presence of large differences in promotion chances and in recorded absence between men and women, our results suggest that these differences are not because of differential incentive responses. Section VI concludes the article with a discussion.

II. Theory

Tournaments offer fixed prizes and are set up in such a way that the probability of winning a prize is a positive function of effort. For firms in a perfectly competitive industry, an optimal tournament is one that generates economic profits of zero and elicits the first-best level of effort (for which the marginal social cost of effort is equal to its marginal social benefit).

Consider a tournament for promotion from level l in the hierarchy to level $l+1$ and suppose initially that there are only two contestants, i and j. Let W_{l+1} represent the reward to the winner, and W_l the reward to the loser. Then $W_{l+1} - W_l$ represents the prize spread. The probability that contestant i wins the tournament is a function of i's own effort μ_i and also of his rival j's effort μ_j. The contestants are unable to control the outcome exactly. They both may be lucky or unlucky, and the luck they experience may affect them individually or jointly. Denote the luck experienced by individual k by $\varepsilon_k, k = i, j$, and suppose that the difference in the contestants' good or bad fortune, $\varepsilon_j - \varepsilon_i$, has cumulative distribution function (CDF), G, with associated probability density function (PDF), g. Then the probability that i wins the tournament is a function of both contestants' effort and both contestants' luck, $P(\mu_i, \mu_j; \varepsilon_i, \varepsilon_j)$ with $\partial P/\partial \mu_k > 0$, $k = i, j$. Suppose, too, that the cost of effort to k is convex in effort and denoted $C_k(\mu_k)$ with $C' > 0$ and $C'' > 0$. The optimal effort supply of k is then determined by:

$$(W_{l+1} - W_l)\frac{\partial P}{\partial \mu_k} = C'(\mu_k). \tag{1}$$

The probability that i wins in a contest against an identical opponent j is the probability of the event that her output is greater:

$$\Pr(\mu_i + \varepsilon_i > \mu_j + \varepsilon_j) = \Pr(\mu_i - \mu_j > \varepsilon_j - \varepsilon_i) = G(\mu_i - \mu_j). \tag{2}$$

Therefore, $\partial P/\partial \mu_k = g(\mu_i - \mu_j)$. In equilibrium the effort of the competitors is the same, so that $\partial P/\partial \mu_k = g(0)$. The equilibrium effort supply for two identical individuals competing against each other is thus:

$$(W_{l+1} - W_l)g(0) = C'(\mu_k),\ k = i, j. \tag{3}$$

In this framework higher pay spreads are associated with higher effort levels through the convexity of the cost function.[1]

[1] Although, as Gibbs (1994) points out, this empirical regularity is not a unique implication of tournament theory. Other similar promotion-based incentive mechanisms would also have this implication. One of the main alternative mechanisms is to promote workers who achieve a given standard. Lazear and Rosen (1981) suggest that in the context of managerial promotion, measurement difficulties might hinder the construction of promotion standards.

Profit maximization with this effort supply and the competitive zero profit condition implies an optimal prize spread.[2] Potentially, this creates an endogeneity problem for our analysis, because we use prize spread and a measure of "importance of luck" as explanatory variables. However, we view our measure of prize spread as weakly exogenous because the time scale over which these quantities are determined is longer than that over which individual workers make their effort decisions. Our measure of the importance of luck is estimated using data from an earlier time period than the one for which we estimate the effort equation. It is thus a predetermined variable.

III. Data

The data are drawn from a database constructed from the personnel records of a major British financial sector firm. A more complete description of the data set and of the characteristics of the firm's personnel policy can be found in Treble et al. (2001). The firm varies in size over the time that we observe it, but it has around 40,000 full-time employees and 20,000 part-time employees. We have data from the personnel and payroll archives that have been maintained since 1988, referring to the firm's British operations. Our data run from January 1989 to March 1997, giving 99 monthly observations. Each observation includes an employee ID number, age, sex, marital status, number of children, ethnic origin, job code, work unit code, salary, bonus, hierarchical grade, date of entry into current spell of employment, performance rating, partial post code of home and work, and, for those employees at their post in March 1991, some indicators of educational attainment. From April 1991 onward, we also have a daily record of attendance. This is coded according to the putative reason for any days not worked, so that absence that is claimed to be because of sickness can be separated from other varieties of absence (e.g., maternity and jury service). We cannot, however, observe when individual workers took their holidays. These are recorded in the event histories as attendance days, but by definition an absence cannot occur. However, since holidays are unlikely to vary either substantially or systematically across individuals, and also since they will on average constitute only 6% of time, the measurement error induced will be negligible.

The firm operates a well-defined internal labor market (Treble et al. 2001). The organizational hierarchy is composed of 14 levels or grades. Two of these grades we ignore. They are reserved for people who are either not part of the hierarchy or have not for some reason been assigned

[2] For details, see McLaughlin (1986). Although not a major focus of the literature, it is also true that firms can make choices that influence the distributions of individual-specific luck that is experienced by workers in the promotion system (Viscusi, Zeckhauser, and O'Keefe 1984).

to a grade. Of the remaining 12 grades, we have ignored people in the lowest four, since these are training grades in which promotion is more geared to the attainment of a standard than to demonstrated superiority over rival employees. Our analysis does not use the top three grades, since they are sparsely populated, and we analyze the behavior in the six grades 5–10, information on grade 11 being included to define the prize for people in grade 10.

Pay comprises a base salary plus a performance-related bonus. In the period we are examining, approximately 25% of the workforce received an annual bonus, assessed using annual appraisals both of the employees themselves and of the units to which they were assigned. Five different appraisal ratings are possible: "outstanding" (5) is the best, followed by "very good," "satisfactory," "not fully effective," and "unsatisfactory" (1), respectively. In practice, employees rarely receive evaluations below satisfactory. At any one time there are quite a large number of employees who have no rating. This is because of a lag between a hire or promotion and the first appraisal in the new job.

In our analysis we interpret the absence rate as a measure of worker effort. Flabbi and Ichino (2001) provides a precedent for this approach, but nevertheless it requires justification. Tournament theory is based on the idea that a worker's effort μ_i and observed output q_i are related by

$$q_i = \mu_i + \varepsilon_i, \tag{4}$$

where ε_i is a random error. The error can be interpreted in a number of ways. It includes the inability of the worker to control perfectly the production process for which he is being rewarded. It might also include errors in measurement of the worker's output. These are (at least partially) controllable by the firm. By devoting more resources to output measurement, the firm can make fewer errors in relative performance measurement.

If a worker is absent on a particular day, output, q_i, is zero for that day. Absence and output are therefore inversely related. Absence is also clearly related to the health state of the worker, but provided that ill health arrives stochastically, the basic assertion remains unchanged: the higher a worker's absence rate the lower, in expectation, is their productive effort over the period to which equation (4) relates.

Consider the following simple model for an individual's absence rate r_i. Suppose that a worker's absence rate is determined by their health status, Θ_i (where "high" Θ_i indicates a "good" health state), and their effort, μ_i, by a function f:

$$r_i = f(\mu_i, \Theta_i) \quad f_\mu < 0 \quad f_\Theta < 0. \tag{5}$$

Assuming that the individual's health state is distributed over the pop-

Table 1
Absence Rates by Performance Evaluation, 1993 and 1994

Supervisor's Rating	1993 Cases	1993 Deviation of Absence Rate from Mean (%)	1994 Cases	1994 Deviation of Absence Rate from Mean (%)
Unsatisfactory	57	79.51	67	138.51
Not fully effective	88	5.21	335	16.89
Satisfactory	10,780	14.77	9,291	18.85
Good	11,963	−5.21	12,605	−7.09
Excellent	5,139	−16.16	5,978	−12.37
Not rated	3,913	−4.89	3,664	−7.30

ulation according to some PDF, $g(\Theta)$, we can derive the marginal function:

$$r_i = h(\mu_i) = \int_{-\infty}^{\infty} f(\mu_i, \Theta_i) g(\Theta) d\Theta, \tag{6}$$

and since $g(\Theta) > 0$ for all Θ (as it is a PDF), $f_\mu < 0 \Rightarrow h_\mu < 0$. It is also true that the inverse function is negatively sloped:

$$\mu_i = h^{-1}(r_i) \quad h_r^{-1} < 0. \tag{7}$$

Thus, absence can be used as a proxy for (negative) effort.

To support this theoretical argument, in table 1 we report cross-tabulations of the absence rate of individuals and supervisors' evaluations, which might be viewed as a more direct measure of effort as perceived by a supervisor. The cross-tabulations reveal a clear inverse relationship between absence rates and performance evaluations. We do not use the evaluations directly as our effort measure because they are recorded only at annual intervals, whereas the absence record is daily.

Simple cross-tabulations do not, of course, condition for other potential effects on ratings. Results of an ordered logit model for performance ratings are reported in table 2. Here, the ordered outcomes are the five categories from "unsatisfactory" to "excellent," giving four estimated cut-off points $\Theta_i, i = 1, \ldots, 4$. On the right-hand side appear the deviation of the absence rate from the mean for the grade (defined formally below) and dummies for gender and grade, age, tenure, tenure in grade, and the size of overtime payments. The results confirm the impression given by the cross-tabulations in table 1.

The empirical work reported below involves three separate estimations, each of which uses a separate subset of the whole data set. First, the main estimation is an effort equation where we model the worker's absence histories. The estimation is by a maximum likelihood random effects

Table 2
Ordered Logit of Supervisors' Ratings

Variable (Mean)	Coefficient	SE
Δr (.0003143)	−2.7428	.2281
Gender (.5304)	.5898	.0312
Grade 6 (.2761)	.7812	.0350
Grade 7 (.1726)	−2.1803	.0462
Grade 8 (.0931)	−1.4329	.0578
Grade 9 (.0580)	−.7694	.0666
Grade 10 (.0179)	−.2976	.1022
Age (36.53 years)	.0500	.0163
Age^2	−.0008	.0002
Tenure (15.92 years)	.0269	.0084
Tenure^2	−.00062	.0002
Month in grade (4.04 years)	.0447	.0061
$(\text{Month in grade})^2$	−.00012	.000073
Overtime (£33.00)	.0015	.000015
Θ_1	−4.5073	.3285
Θ_2	−2.2563	.2936
Θ_3	1.8279	.2901
Θ_4	4.3039	.2917
Log-likelihood = −21,622.89		

NOTE.—N = 22,714. The proportions in rating categories are: rate = 1: .0018, rate = 2: .0146, rate = 3: .3245, rate = 4: .4249, and rate = 5: .2342.

model (with unobserved effects integrated out numerically) and incorporates a variation of Chamberlain's (1980) method of correction for bias resulting from the correlation of the unobserved component on the observed regressors. The computational burden of this is heavy, and so we have used a randomly selected sample of 998 individuals from the set of individuals who were employed in grades 5–10 at some time between January 1992 and December 1993. The data used refer to this sample's behavior every month during that same period. This gives an unbalanced panel of data with $N = 998$ and $T_i \leqslant 507$ for all i. A table of summary statistics is given as appendix table A1.

Second, the right-hand-side variables in the main estimation include a measure for each individual of $g(0)$, calculated from a subsidiary equation described in detail in Section V below. The equation models promotion as a function of a number of characteristics of individuals and their jobs. The subsidiary equation uses information for the period from April 1991 to December 1991 (i.e., prior to that used in the main estimation) in order to avoid endogeneity problems. We use the largest possible sample in order to be sure that there is sufficient information to obtain a precise estimate for each possible type of individual. However, the individuals included in the sample used for the main estimation are omitted to avoid any possible contamination. This gives us a sample of 27,758, which, since the time window is short, is treated as a cross-section. A simple logit technique is used for estimation. Appendix table A2 provides summary statistics.

Third and finally, we use Orme's (1997) technique to check for initial conditions bias in the main panel estimation. This involves creating generalized residuals from a subsidiary estimation, which are then included in the main estimation. The details are discussed in Section IV.C. This estimation can only be done using individuals who are already employed in grades 5–10 at the start of January 1992, since there are no initial conditions applying to those joining the sample after this. Accordingly, we use the entire cross-section of 24,283 individuals employed at January 1992 to carry out the subsidiary estimation required by Orme's technique. Appendix table A3 provides these summary statistics.

Our use of the available data is thus driven by the competing claims of the avoidance of endogeneity bias, maximal precision, and computational tractability. The main estimation uses a panel with a 2-year span, the start date of which is determined by the need to reserve some information for the construction of the luck variable. April 1991 is the start of recorded absence data. We use the first 9 months for the estimation of $g(0)$, and the following 2 years for the main equation.

IV. Econometric Model

A. Basic Structure

The theory outlined in Section II predicts that effort will be related to a number of characteristics of individuals and their work contracts. In the empirical part of the article, we treat daily absences as an indicator of effort. Accordingly, we model the incidence of absence using a latent variable structure to generate the observed binary absence event history.

Let

$$d_{it} = \begin{Bmatrix} 1 & \text{if} & d_{it}^{*} > 0 \\ 0 & \text{if} & d_{it}^{*} \leqslant 0 \end{Bmatrix}, \tag{8}$$

where

$$d_{it}^{*} = \beta' x_{it} + \gamma d_{it-1} + \sigma u_i + v_{it}; i = 1, \dots, N;\ t = 1, \dots, T_i. \tag{9}$$

According to this structure we observe the binary variables representing absence ($d_{it} = 1$) or attendance ($d_{it} = 0$) at various times t for N individuals indexed by i. The attendance decision is determined for each individual by the value of the latent variable d_{it}^{*}. This is assumed to be a function of a p-vector of observed independent variables, x_{it}, and the lagged attendance indicator, d_{it-1}. The error has a components-of-variance structure, with u_i representing a time-invariant, individual-specific unobserved component, and v_{it} is the remaining error. Parameter vectors β, γ, and σ have conformable dimensions p, 1, and 1, respectively.

Assuming that u_i is a realization of a random variable u with PDF

$h(u)$ in the population, a marginal likelihood can be formed by integrating out u in the following way:

$$\ln(\beta, \gamma) = \sum_{i=1}^{N} \ln \int_{-\infty}^{\infty} \prod_{t=2}^{T_i} [F(\beta' x_{it} + \gamma d_{it-1} + \sigma u)]^{d_{it}} [1 - F(\beta' x_{it} + \gamma d_{it-1} + \sigma u)]^{1-d_{it}} h(u) du, \quad (10)$$

where F is the CDF corresponding to v_{it}. The unobserved term, u, is assumed to be distributed as a standard normal variate, and estimation can be performed by the SABRE software developed by Barry, Francis, and Davies (1990).

B. Construction of $g(0)$

The theory outlined in Section II predicts that effort depends on the spread of wages between grades and also on luck. We compute wage spread directly from the data (as the difference in the mean pay plus bonuses in adjacent grades), but measuring $g(0)$ is more difficult. In tackling this problem, we use prior information about the promotion of individuals to calculate a measure for each type on a rich menu of different individual types. Suppose, for instance, that an adequate description of individuals specifies their gender, grade, and performance rating. Suppose further that promotion decisions take account of these three variables only, in addition to luck. Then the influence of luck for each distinct type can be gauged from the residuals of a logit regression of promotion on gender, grade, and performance rating. The three independent variables give $2 \times 6 \times 5 = 60$ different types of individual, for each of which an estimate of $g(0)$ can be computed. The specification adopted below is, of course, richer than in this illustration.

Specifically, we estimate a logit model, in which the dependent variable describes whether or not a worker was promoted between April 1991 and December 1991. On the right-hand side are:

a) a set of dummy variables for grade (omitted category: grade 5);
b) a dummy variable for gender (omitted category: male);
c) interactions between the grade and gender dummies;
d) a set of dummy variables for performance rating (omitted category: "satisfactory" or worse); and
e) the employee's absence record relative to that of other employees in the same grade.

The estimation uses data for the whole population of 28,756 full-time workers employed at April 1991, excluding the 998 workers used to estimate the main effort equation. The period is chosen since it precedes

Table 3
Promotion Logit

Variable (Mean)	Coefficient	SE
Constant	−2.7477	.0888
Grade 6	−.3646	.0905
Grade 7	−.0034	.0978
Grade 8	.0577	.1059
Grade 9	−1.3381	.1823
Grade 10	−.9981	.2279
Gender	−.6362	.0779
Gender × grade 6	−.0211	.1250
Gender × grade 7	.0541	.1571
Gender × grade 8	.3651	.2356
Gender × grade 9	1.2125	.4953
Gender × grade 10	.8286	.7625
Δr	−6.6017	.8379
Rate 4	.7939	.0713
Rate 5	1.0645	.0866
Unrated	.5367	.0845
Log-likelihood	−6,806.5496	

NOTE.—$N = 27{,}758$.

the 2-year period for which we analyze the absence data and thus obviates any possible endogeneity problem.

The absence variable is constructed using the recoded absence rate, r_i, of each individual. This is the number of days absent during the 9 months to December 1991 divided by the number of contracted days. From each individual's absence rate, we subtract the mean absence rate calculated for all other employees in the same grade, l_i, as employee i, $\bar{r}_{l_i} = \frac{1}{n_{l_i}} \sum_{i \in l_i} r_i$ to create $\Delta r_i = r_i - \bar{r}_{l_i}$.

Using equation (2), we can write the probability of winning the contest for an individual with characteristics y_i as

$$G(\Delta r_i; y_i) = L(\psi' y_i + \Theta \Delta r_i), \tag{11}$$

where L is the logistic function. Differentiating this expression with respect to $-\Delta r_i$ (our measure of effort) and setting Δr_i equal to zero gives our estimator for $g(0)$:

$$\overline{g(0)} = \frac{\partial G}{\partial \Delta r} = -\Theta L'(\psi' y). \tag{12}$$

The results of the logit estimation are given in table 3. The promotion probability from grade 6 to grade 7 is significantly lower than from grade 5 to grade 6. This is because a promotion from grade 6 to grade 7 marks the qualitatively significant transition from clerical to managerial status. The probability of promotion is also low at the very top of the hierarchy. Women overall have lower promotion probabilities than men, but these differences are concentrated in the clerical and lower managerial grades.

These findings are consistent with results from the data set reported in Treble et al. (2001) and with results from a different data set reported by Jones and Makepeace (1996). High performance ratings improve promotion chances, and high absence rates reduce them, as one would expect. Rather more subtle is the significant improvement in promotion chances for unrated employees. These employees are nearly all recent promotees, and the result echoes the findings of Bridges (2004) on fast-track effects in this same data set. The idea of a fast track is that promotion is easier to obtain for recent promotees than for other observationally identical individuals. This may be because of missing relevant information in the model or could be evidence of the existence of a biased contest.

However that may be, the main point of the estimation in table 3 is to enable the computation described in equation (12) to be done. Summary statistics of the resulting series are included in table A2.

C. Two Technical Problems

Two potentially important technical problems arise with the econometric structure as specified. First, the existence of a lagged endogenous variable in the specification gives rise to an initial conditions problem, which can cause bias in panel estimators (Hsiao 1989). Second, the unobserved component u is not necessarily independent of observed regressors. To the extent that u reflects motivation, morbidity, or other long-term factors influencing work performance, then we can a priori expect it to exhibit dependence with certain included regressors, in particular with grade. Once again, this induces a potential inconsistency in the estimator. We discuss these problems in turn.

1. *Initial Conditions Problem*

The initial conditions problem is unlikely to be serious since such biases are known to be most serious in short panels, and our data has a large time dimension ($T = 507$). For completeness, we use the method suggested by Orme (1997) to check for potential inconsistency. Orme's method begins by assuming that the initial condition, which in our case is the choice of absence at time $t = 1$, can be modeled as

$$d_{i1}^{*} = \lambda' y_i + \eta_i, \tag{13}$$

where y_i is a vector containing current and/or presample values of regressors. The event $d_{i1} = 1$ is the same as the event $d_{i1}^{*} > 0$. Assuming bivariate normality between u_i in equation (9) and η_i, Orme shows that

$$E(u_i | d_{i1}) \equiv e_{i1} = (2d_{i1} - 1)\frac{\Phi(\lambda' y_i)}{\Phi(\{2d_{i1} - 1\}\lambda' y_i)}, \tag{14}$$

which is a probit generalized error. Thus, $\sigma u_i = \sigma\rho e_{i1} + v_i$, where v_i is an

Table 4
Initial Conditions Probit

Variable	Coefficent	SE
Constant	−1.2728	.1237
Grade	−.1083	.0190
Gender	.2595	.0372
Age	−.0180	.0126
Age^2	−.0002	.0002
Gender × age	−.0120	.0044
Grade × age	.0016	.0020
Log-likelihood	−3,854.68	

NOTE.—N = 24,283.

error term uncorrelated with d_{i1}. Substituting in equation (8) suggests an estimation procedure where the e_{i1} are replaced by their predictions $\overline{e_{i1}}$ and added to the regressor set. The equation used to generate the estimated generalized residuals included grade, gender, age, and interactions of age with grade and gender. Age is entered nonlinearly and acts as identifying information. The result of the estimation is shown in table 4.

2. *Dependency of Unobserved Component on Observed Regressors*

To allow for the likely dependency of the unobserved component on the observed regressors, we follow the procedure suggested by Chamberlain (1980). The unobserved term, u, in equation (9) captures the effect of individual-specific unmeasured factors such as motivation and morbidity on the probability of absence. Chamberlain's method models the correlation between e_{i1} and the observed regressors by allowing the individual-specific effect to depend linearly on the values of the regressors during the whole period of the data.

Let z_{it} be a q-dimensional subvector of the included regressors, x_{it}. Then write u_i as

$$u_i = \sum_{t=1}^{T_i} \alpha_t' z_{it} + \eta_i, \tag{15}$$

where α_t is a conformable $q \times 1$ parameter vector. It is important to note here that the summations are over t, so that future values of regressors are allowed to be informative about the occurrence of a current event.

Since T is large, using equation (15) unmodified would involve estimating a large number of extra parameters. Greater parsimony can be achieved by assuming α to be time invariant and factoring it out of the above expression to give

$$u_i = \alpha T \frac{\sum_{t=1}^{T_i} z_{it}}{T} + \eta_i, \tag{16}$$

Table 5
Estimates of Logistic Mixture Model for Effort (Absence Histories)

	Specification 1		Specification 2		Specification 3	
Variable	Coefficient	SE	Coefficient	SE	Coefficient	SE
Constant	−3.4104	.3423	−3.3972	.3612	−2.9920	.5070
Lag absence	4.8213	.0242	4.8211	.0242	4.8200	.0243
Pay spread/10,000	−.2026	.0941	−.2033	.0940	−.2010	.0951
$\overline{g(0)}$	−.3702	.1560	−.4083	.1927	−.4172	.1881
Gender	.3016	.0615	.2578	.1989	.2490	.1973
Gender × $\overline{g(0)}$			.1143	.3165	.0871	.3159
Gender × pay spread/10,000			−.0119	.1501	.0078	.1523
Lower management	.1298	.0967	.1288	.0958	.1086	.0924
Higher management	.5209	.2159	.5105	.2169	.4650	.2143
Age					−.0242	.0215
Age^2					.0003	.0003
Mean grade	−.2214	.0592	−.2200	.0596	−.2166	.0597
e_1	.1338	.5003	.1533	.5154	.1930	.5269
σ (scale parameter)	.7520	.0199	.7516	.0198	.7545	.0197
Log-likelihood	−34,784.9800		−34,784.8905		−34,784.2785	

where α is now a scalar, and the expression has been rewritten as an expression in the means of the z_{it}.

Chamberlain's method, employed in this way, can be interpreted as allowing the mean of the distribution of the unobserved component to shift by a linear combination of the means (taken over time) of the variables with which it is believed to be correlated. In the estimates reported, we included a single variable, the grades occupied by each individual from time to time during the 2-year window of our data, as the z_{it}, thus allowing the distribution to shift by a linear multiple of mean grade.

The empirical procedure can be interpreted in the following way: for any given individual, mean grade over time can be interpreted, ceteris paribus, as an indicator of long-term unobserved determinants of absence behavior such as motivation, morbidity, or household structure. Incorporating mean grade as a regressor shifts the mean of the distribution of the unobserved term for each individual.

V. Results

The estimates of the marginal likelihood model described in equation (10) are reported in table 5. The data used are an unbalanced panel of 998 employees observed monthly over 2 years from January 1992. The specification adopted is greatly influenced by a perceived need for parsimony in order to handle the computational burdens imposed by the estimation procedure. Right-hand-side variables are:

a) the two variables of interest: pay spread (scaled by a factor of 10^{-4}) and luck ($\overline{g(0)}$);
b) a dummy for gender;
c) in specification 2, interactions between the variables of interest and

gender;

d) in specification 3, age entered quadratically;

e) a simplified dummy structure for grade consisting of a lower management indicator (grade 7 or 8 = 1) and a higher management indicator (grades 9 and above = 1). The omitted category is clerical grades 5 and 6. All these represent the grade occupied by the employee in January 1992 or at the date of entry into the firm, whichever is earlier;

f) the Chamberlain correction term (mean grade) described in Section IV.C.2; and

g) the Orme generalized residual ($\bar{e}_1$) described in Section IV.C.1.

Table 5 also reports estimates of the scale parameter (σ) in the mixture model.

The estimated Orme generalized residual, $\bar{e}_1$, is insignificant in equation (10), suggesting that the length of the panel is sufficiently long to render any initial conditions bias negligible.

Turning to the substantive results, note that since the dependent variable is a measure of absence, a negative coefficient on a right-hand-side variable implies that an increase in the value of that variable increases effort supply. Thus, increasing pay spread increases effort, as does increasing $g(0)$. In the latter case, since $g(0)$ is the height of a density function, we conclude that the evidence implies that the less important luck is in determining promotion decisions, the greater the effort that workers will put in to secure a promotion. Both of these results are consistent with a tournament view of the world. The latter result, in particular, is as far as we know new, and it has the important interpretation that capricious decision making in the context of promotion has quantifiable incentive effects, over and above its implications for misallocated resources.

We find support for the two main empirical regularities predicted by tournament theory, but we also find that there are differing effects between the genders. It is now a commonplace observation that absence rates are higher among women than among men (see, e.g., Barmby, Ercolani, and Treble 1999, 2002). This is confirmed in this data, but our results also show that women do not react differently from men in their responses to the incentives provided by the reward structure and the promotion system. Neither interaction term has a statistically significant effect. This suggests that the differences between men and women's absence rates (or, more speculatively, work effort) are not generated by differential responses to incentives, but by selection effects.

A contrasting conclusion is reached with respect to seniority in the hierarchy. Table 5 shows that higher management actually are *more* likely to be absent than other grades, when controlling for the incentive effects of pay spread and luck. Again, this seems like an important observation:

senior managers' behavior in this organization, according to this evidence, is actually very heavily influenced by incentive systems of pay and promotion, so much so that the raw differential in absence behavior is reversed when controlling for the effect of incentives.

VI. Conclusion

We see the main contribution of the present article as methodological. We have taken the ordinary administrative records of a large firm and developed a way of using them to cast light on various aspects of incentive schemes and selection. We have also exploited our panel data to construct an individual-specific measure of the importance of luck in the promotion process.

The substantive results of our investigation are also of considerable interest but should probably be treated with caution until confirmed by evidence from other firms and contexts. In summary, they are that men's and women's reactions to the incentives provided by pay and promotion are indistinguishable. The large and robust gender differences displayed in raw data are therefore not because of incentives. We need to look elsewhere for an explanation. Similarly large and robust differences in absence behavior between different levels of the hierarchy are actually reversed when the effect of incentives is factored out. This poses a rather different, but equally intriguing, challenge to future research.

Appendix

Summary Statistics

Table A1
Summary Statistics for Sample Used in Main Estimation

Grade	Number (January 1992)	Absence Rate (%)	Mean Pay (£)	Mean Bonus (£)	Mean Promotion Rate (%)	Proportion Female (%)	Mean Age	Predicted g(0)
5	388 (38.8)	3.56	11,879	2.54	14.95	76.29	30.92	.4602
6	259 (25.9)	3.36	14,715	32.20	13.90	57.53	35.15	.3947
7	190 (19.0)	2.21	18,604	625.37	10.00	32.11	34.92	.4120
8	92 (9.2)	1.74	24,749	892.87	18.48	16.30	38.75	.4808
9	53 (5.3)	1.46	36,628	2,219.2	7.55	9.43	41.47	.1567
10	16 (1.6)	.56	47,721	4,215.6	.00	.00	46.66	.2166

NOTE.—$N = 998$; $T = 507$. Numbers in parentheses are percentages.

Table A2
Summary Statistics for Sample Used in Subsidiary Promotion Logit Estimation

Grade	Proportion of Sample (%)	Proportion Female (%)	Proportion Rated 4 (%)	Proportion Rated 5 (%)	Proportion Unrated (%)
5	38.04	77.79	44.09	19.98	19.82
6	24.93	55.87	36.06	29.24	22.71
7	19.66	29.20	12.88	.48	10.03
8	9.45	13.92	21.43	.80	7.51
9	5.65	7.21	30.06	1.34	12.76
10	2.27	6.66	38.35	3.49	15.06

NOTE.—N = 27,758.

Table A3
Summary Statistics for Sample Used in Subsidiary Initial Conditions Probit Estimation

Grade	Proportion of Total (%)	Proportion Female (%)	Age (Years)	Mean Rate of Absence (%)
5	38.23	76.76	33.19	5.50
6	26.69	56.52	37.19	3.55
7	19.16	28.80	37.57	2.69
8	8.93	13.38	41.00	2.12
9	5.35	6.86	43.06	1.08
10	1.65	4.75	45.06	1.50

NOTE.—N = 24,283.

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