Human Capital and Institutional Determinants of Information Technology Compensation: Modeling Multilevel and Cross-Level Interactions

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Compensation is critical in attracting and retaining information technology (IT) professionals. However, there has been very little research on IT compensation. Juxtaposing theories of compensation that focus on human capital endowments and labor market segmentation, we hypothesize multilevel and cross-level determinants of compensation. We use hierarchical linear modeling to analyze archival salary data for 1,576 IT professionals across 39 institutions. Results indicate that compensation is directly determined by human capital endowments of education and experience. Institutional differentials do not directly drive compensation, but instead moderate the relationship of human capital endowments to compensation. Large institutions pay more than small institutions to IT professionals with more education, while small institutions pay more than large institutions to IT professionals with less education. Not-for-profit institutions pay more than for-profits to IT professionals with more or IT-specific education. Further, information-intensive institutions pay more than noninformation-intensive institutions to IT professionals with more or IT-specific education. We interpret these results in the context of institutional rigidity, core competencies, and labor shortages in the IT labor market.
(*Compensation; Hierarchical Linear Modeling; Management of IT Professionals*)

1. Introduction

Rapid innovations in information technology (IT), the rise of the Internet and web-based businesses, and the overall growth of the information economy create challenges for institutions that seek to recruit and retain skilled IT professionals (Ang and Slaughter 2000). Despite the recent collapse of new dot.com businesses and the slowing of growth in the high-tech industry, the demand for skilled IT professionals remains strong. In the United States alone, more than 2 million people are employed in the IT profession, and an additional 1.4 million more computer scientists, systems analysts, and programmers will be needed by 2003 (U.S. Department of Commerce 1998). Worldwide, the shortage of IT professionals stands at more than 1 million. The imbalance in the supply and demand for IT professionals contributes to the length of the backlog for IT services, the high turnover rates of IT professionals, and IT skills shortages. Thus, institutions are challenged to develop effective recruitment and retention strategies for their

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IT professionals, given these characteristics of the IT labor market.

Although compensation is identified as a critical lever in attracting and retaining IT professionals, there has been relatively little examination of compensation strategies for IT professionals. Our objective in this study is to identify the determinants of IT compensation. This research makes two important contributions to knowledge. First, our study represents the first in-depth analysis of compensation for IT technical professionals. Despite the importance of compensation in attracting and retaining IT professionals, to date, very few studies of compensation have been conducted on IT professionals. These studies include Talmor and Wallace (1998), which investigates the determinants of compensation for CEOs in IT firms, and Anderson et al. (2000), which examines compensation strategies for top IT executives in publicly listed IT and non-IT firms. However, the factors that determine IT executive compensation do not necessarily determine compensation for nonexecutives. Thus, our study contributes to this stream of research by focusing on compensation strategies for nonexecutive IT professionals who perform complex, technical assignments that require originality, independent judgment, and analytical skills. We capitalize on our unique access to a comprehensive archive of compensation data for 1,576 IT technical professionals across 39 institutions of varying size, industry, and sector profiles.

Second, our study contributes to existing theories of compensation by hypothesizing and empirically testing cross-level determinants of compensation. Prior studies of compensation have largely focused on studying compensation strategies at a single level of analysis. Early research was conducted by economists who developed theories of human capital and focused on the individual determinants of compensation (e.g., Becker 1975, Mincer and Polachek 1974). Later research by sociologists drew upon macrolevel theories of organizational sociology and argued for institutional determinants of compensation (e.g., Brown and Medoff 1989, Groshen 1988, Kalleberg and Van Buren 1996). Research in the early to mid-1990s began to model the determinants of compensation at multiple levels of analysis, where the independent contribution of individual- and institution-level predictors was examined (e.g., Gerhart and Milkovich 1990, Stroth et al. 1996). Even so, no attempt has been made to theorize and model the interactive effects of the individual- and institution-level determinants, i.e., the *cross-level interactions* (Hofmann 1997). We believe this is not because cross-level determinants are unimportant, but because of limitations in conventional ordinary least-squares techniques for the estimation of models with nested data structures. However, recent advances in hierarchical linear modeling (HLM) (Hofmann 1997, Bryk and Raudenbush 1992) permit tractable and efficient estimation of the cross-level determinants of social phenomena. In this study, we use the power of HLM to evaluate a theoretical model of compensation that embraces not only individual- and institution-level determinants, but also cross-level determinants of compensation.

Our paper proceeds as follows. We juxtapose theories of compensation to formulate hypotheses about individual-, institution-, and cross-level determinants of compensation. We evaluate our hypotheses empirically, using archival salary data on 1,576 IT professionals across 39 institutions, and employ HLM to estimate the multilevel determinants of compensation. We interpret our results in light of institutional rigidity, core competencies, and labor shortages in the IT profession, and conclude with directions for future research on IT compensation.

2. Human Capital, Institutional, and Cross-Level Determinants of IT Compensation

2.1. Human Capital Determinants

Human capital theory suggests that differences in compensation reflect differences in human capital endowments among workers. *Human capital endowments* refer to worker attributes such as education and experience (Becker 1975, Mincer 1970). These attributes reflect the level of an individual's investments in formal education in school or on-the-job work experience. Hence, higher education or longer work experience warrant higher compensation. In the IT profession, both education and IT work experience are important attributes of human capital. IT jobs are complex, requiring knowledge of difficult technical concepts such as data modeling, process engineering, and design theory. Such general knowledge is often acquired through advanced educational degrees. In addition, the application of IT to organizational problems involves a high degree of tacit or specific knowledge about organizational systems, roles, and procedures that is acquired through work experience at an institution and in the IT profession (Stinchcombe and Heimer 1988). Accordingly, we hypothesize that,

Hypothesis 1a. *IT compensation is positively related to education.*

Hypothesis 1b. *IT compensation is positively related to experience.*

2.2. Institutional Determinants

The human capital theory focuses on labor supply factors. In contrast, the neoinstitutional or structuralist theories (Leontaridi 1998) focus on labor demand factors. According to the neoinstitutional perspective, the labor market is not a single, homogeneous, competitive market. Rather, there are features of the institution or industry that can affect the variation in compensation (Segal 1986). Typically, explanations for institutional differentials have centered on segmenting the labor market based on institution size (Brown and Medoff 1989, Kalleberg and Van Buren 1996), which is a surrogate for institutional power (Borjas 1980), institutional demography such as age (Stewman and Konda 1983), unionization (Bamberger and Admati-Dvir 1995), profit orientation such as for-profit versus not-for-profit (Gerhart and Milkovich 1990), or degree of information intensity (Palmer and Griffith 1998). In our study, we examine size, profit orientation, and information intensity as institutional determinants of compensation. Institutional demography is not analyzed, as there is little variance in the age of the institutions included in the study. Similarly, there are no differences with respect to unionization, as the IT jobs we analyze do not fall within the purview of unions.

2.2.1. Size. Many studies have found a positive relationship between institutional size and the level of compensation (Bailey and Schwenk 1980, Brown and Medoff 1989, Evans and Leighton 1988, Mellow 1982, Villemez and Bridges 1988). Literature reviews by Brown and Medoff (1989) and Kalleberg and Van Buren (1996) identify the theoretical reasons for this positive relationship. First, large institutions have a higher ability to compensate because of their greater market power and therefore higher rate of return on capital. Second, large institutions face greater complexity and thus need workers who have greater expertise (Becker 1975, Fisher and Govindarajan 1992). Third, worker shirking is more of a problem in large institutions because it is more difficult to monitor performance. With higher compensation, shirking is reduced because employees realize they would be unlikely to find another job that compensates as well (Shapiro and Stiglitz 1984).

In the context of IT, large institutions will offer higher compensation to IT professionals because these institutions possess greater financial resources. Furthermore, given the greater uncertainties and complexities of information systems development in large institutions, coupled with the difficulty in performance monitoring of IT professionals (Ang and Beath 1993), it is likely that large institutions will pay higher compensation to their IT professionals. Thus,

Hypothesis 2a. *IT compensation is higher in larger than in smaller institutions.*

2.2.2. Profit Orientation. Research by Krueger and Summers (1988) and others has shown significant effects of sector on compensation. One key labor market segmentation is profit orientation. Not-for-profit institutions are an important segment of the labor market, as they increasingly account for a significant portion of paid employment in an economy (Roomkin and Weisbrod 1999, Ruhm and Borkoski 2000). Prior empirical research on compensation in not-for-profit institutions reveals that workers in not-for-profits receive lower average earnings than observably similar individuals working in profit-seeking institutions. For example, Preston (1989) shows that managers and professionals in not-for-profits earn 18% lower hourly wages than their for-profit counterparts after controlling for human capital characteristics and industry.

The differential in earnings is based on several theoretical explanations. One explanation of earnings differentials between sectors is *institutional rigidity*. As Pfeffer and Baron (1988) observe, constraints of personnel budgeting are particularly prominent in not-for-profit institutions. Not-for-profits, including government organizations, have less autonomy due to institutional and civil service rules (Meyer 1982). As such, employees in not-for-profits are assumed to show less initiative and undertake less risk. The shelter of not-for-profits from competitive and dynamic market environments also dampens compensation. Not-for-profit institutions typically do not have much discretion or flexibility in their compensation strategies for a number of reasons. First, not-for-profits are highly accountable to the public for their resource allocation, including compensation strategies (Boyne et al. 1999). There are well-defined scales for compensating employees with different education credentials. Second, concepts of internal equity are especially salient in not-for-profits where the overall compensation strategy is based on a standardized scale (Morrisey et al. 1996). Thus, not-for-profits are restricted in their ability to dynamically adjust compensation scales. In contrast, for-profits operate in a competitive and dynamic environment and can adjust compensation strategies to be more responsive to changes in the labor market.

Another explanation of earnings differentials between sectors is the *labor donation* theory of wages (Handy and Katz 1998, Rawls et al. 1975). Labor donation theory postulates that lower earnings in a not-for-profit institution result when individuals recognize a not-for-profit's lower ability to compensate (vis-à-vis for-profits), and are willing to "donate" a portion of their paid labor to further the social cause of the institution. To illustrate, an empirical study by Frank (1996) of university graduates shows that some have chosen to work in "socially responsible" occupations or companies even though they receive substantially lower wages than their counterparts after controlling for gender, curriculum, and grade point average.

A final explanation for lower salaries in not-for-profits is based on the explanation of nonmonetary perks that individuals receive for working in these institutions. Compensating differentials can include better working conditions, such as a less demanding or less stressful work environment, shorter work hours, or lower risk of job loss (Ruhm and Borkoski 2000).

We expect that in IT, similar to in other occupations, salaries would be lower for IT professionals in not-for-profit than for-profit institutions. IT jobs often involve unpredictably long working hours as well as heavy workloads, leading to exhaustion, stress, and turnover. Thus, nonmonetary perks such as shorter work hours or a less stressful work environment would have considerable value to IT professionals, in effect compensating them for lower salaries in not-for-profits. Further, relative to for-profits, not-for-profits cannot as easily adjust compensation in response to the dynamic labor market conditions for IT professionals. Therefore, we posit that,

Hypothesis 2b. *IT compensation is higher in for-profit than in not-for-profit institutions.*

2.2.3. Information Intensity. In information-intensive industries such as IT, finance, and insurance, the successful deployment of IT in product and service delivery is core to the business (U.S. Department of Commerce 1998). Information-intensive institutions offer products and services that contain high information content and use sophisticated information technologies to deliver these products and services (Palmer and Griffith 1998). Accordingly, information-intensive institutions are employers who regard IT professionals as their core workers. Based on core competency theory (Hamel and Heene 1994), we hypothesize that IT professionals would be compensated more in information-intensive institutions than in noninformation-intensive institutions. Compared with institutions in industries such as manufacturing, oil production, and transportation, where the information or IT content of the products is not as high, information-intensive institutions compete based on the core competencies of their IT professionals (Hamel and Heene 1994). Therefore, the skills and expertise of IT professionals are more crucial to the competitive strategy and survival of information-intensive institutions. This suggests that:

Hypothesis 2c. *IT compensation is higher in information-intensive than in noninformation-intensive institutions.*

2.3. Cross-Level Human Capital × Institutional Determinants

Beyond the independent effects of human capital and institutional factors on compensation, we propose that the strength of the relationship between human capital endowments and compensation varies across different types of institutions, in this case, institution size, sector, and information intensity. It is likely that large institutions pay more than small institutions to individuals with greater human capital endowments. This is because large institutions possess more financial slack to bid for a restricted pool of employees who are highly qualified in terms of their education and abilities (Oi 1983). With greater financial slack, large institutions are also able to pay higher premiums for experienced employees so that the job-specific knowledge gained through work experience is retained within the institution. This is especially true for IT professionals, where the learning-by-doing experiences in developing information systems and in managing projects contribute significantly to the human capital of the employee (Stinchcombe and Heimer 1988). Thus, we expect that:

Hypothesis 3A. *Compensation is higher in larger than in smaller institutions for IT professionals with more education.*

Hypothesis 3B. *Compensation is higher in larger than in smaller institutions for IT professionals with more experience.*

Similarly, we posit that for-profit institutions offer higher compensation than not-for-profit institutions to IT professionals who have higher levels of human capital endowments. This is because for-profit institutions have a greater ability to pay, are more flexible in their compensation strategies, and are less constrained by institutional rules and conflicting goals and demands when competing for a restricted pool of highly qualified IT professionals. Thus, we hypothesize that,

Hypothesis 4A. *Compensation is higher in for-profit than in not-for-profit institutions for IT professionals with more education.*

Hypothesis 4B. *Compensation is higher in for-profit than in not-for-profit institutions for IT professionals with more experience.*

In the case of information intensity, we theorize that information-intensive institutions offer higher compensation than noninformation-intensive institutions to IT professionals with higher human capital endowments. This is because IT professionals are core to the success of information-intensive institutions (U.S. Department of Commerce 1998). Information-intensive institutions must ensure that that their core competencies are not eroded. As IT professionals with high human capital endowments are scarce relative to the overall IT labor pool, it behooves information-intensive institutions to pay more to attract and retain these highly qualified and experienced IT professionals. Accordingly, we expect that:

Hypothesis 5A. *Compensation is higher in information-intensive than in noninformation-intensive institutions for IT professionals with more education.*

Hypothesis 5B. *Compensation is higher in information-intensive than in noninformation-intensive institutions for IT professionals with more experience.*

3. Method

3.1. Research Setting and Archival Data

We test our hypotheses using salary data for IT professionals in Singapore. Well known for its nationwide strategic IT Plan, the Singapore government has the goal of becoming a software leader and has implemented economic incentives to attract major software companies to the country. This has increased demand for IT labor such that there are shortages of qualified IT professionals. Therefore, compensation decisions are very critical components of human resource strategies for IT professionals in Singapore.

We obtained salaries of 1,576 IT professionals from archival data for 39 institutions that participated in the 1997 Information Technology Management Association (ITMA) Salary Survey. The 39 institutions represent 42% of all ITMA members: 19 are information-intensive for-profits (in information and financial services), 10 are noninformation-intensive for-profits (in manufacturing, oil production, aerospace, and transportation), and the remaining 10 are not-for-profits (utilities, educational, government, and charitable institutions). The institutions represent a mix of small and large, ranging in size from 7 to 13,000 employees. Based on chi-square analyses, the 39 institutions in our sample are representative of the larger ITMA population in terms of size ($\chi^2 = 0.58$, $df = 1$, $p > 0.10$), sector ($\chi^2 = 0.12$, $df = 1$, $p > 0.10$), and information intensity ($\chi^2 = 0.22$, $df = 1$, $p > 0.10$).

IT professionals average 7 years of IT work experience, 48% are male, 70% have college degrees, and 60% are IT majors. Twelve percent are project leaders, 22% are senior systems analysts, 28% are systems analysts, and 38% are programmers. Project leaders manage multiple IT projects; senior systems analysts serve as lead analysts on single projects and perform high-level analysis and design tasks; systems analysts work with users to determine requirements and formulate system specifications, and programmers code test, and implement the specifications.

3.2. Constructs and Measures

Our analysis includes two compensation measures: base and total compensation. *Base compensation* is the 12-month salary of an individual, together with any guaranteed bonus for that year. *Total compensation* includes base compensation as well as the variable portion of the individual's total salary. We do not include stock options. Stock options are becoming an increasingly popular form of compensation in the United States, particularly for executives and professionals in IT vendor and start-up institutions (Anderson et al. 2000). The institutions in our sample do not offer stock options to IT professionals.

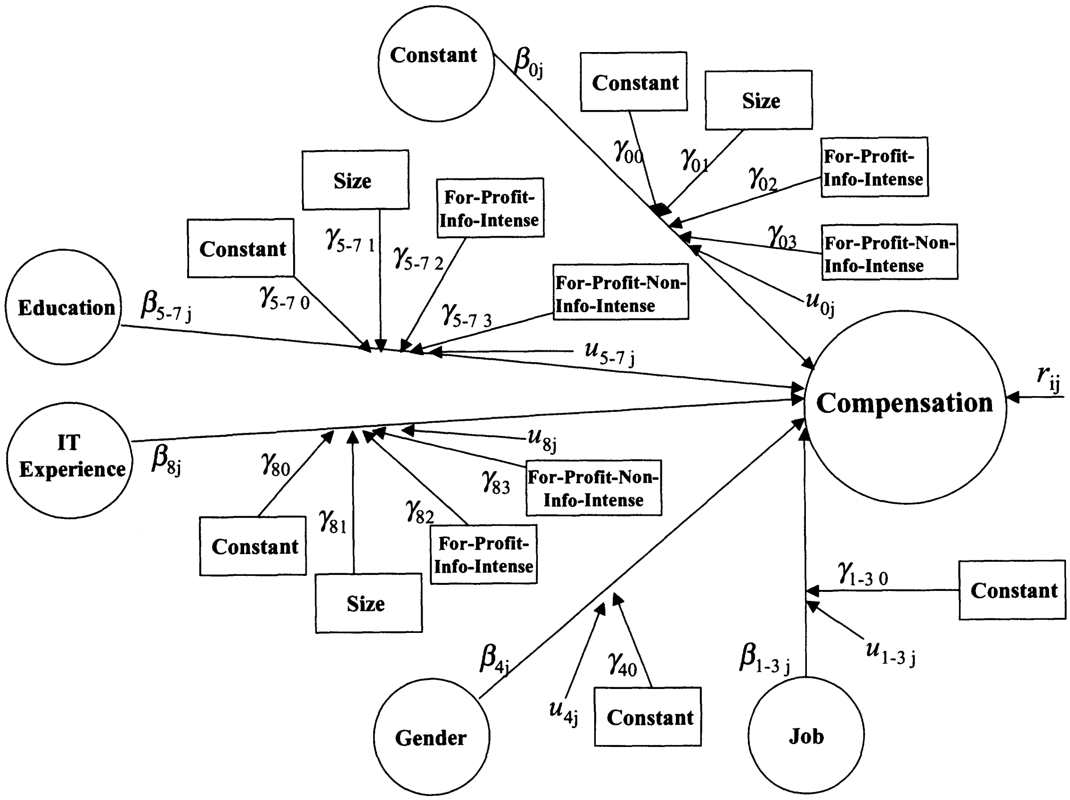
We measure human capital endowments in terms of the level and occupational specificity of education and the years of IT work experience. Education is modeled as a set of binary variables with associate's degree, non-IT major as the base case, and *Education1 (IT-Grad)* to indicate bachelor's degree, IT major; *Education2 (non-IT-Grad)* to indicate bachelor's degree, non-IT major; and *Education3 (IT-non-Grad)* to indicate associate's degree, IT major. *Experience* is a continuous variable that assesses the number of years that the individual has held any IT job (i.e., the total IT labor market experience of the individual, not the tenure in a particular job).[1] Institutional variables measured include size, sector, and information intensity. *Size* is a continuous variable and is measured as the natural logarithm of the number of employees in the institution; the log transform is necessary to correct for skewness of the variable's distribution. Sector and information intensity are modeled as a set of binary variables with not-for-profit institutions as the base case, *FP-II* to indicate for-profit information-intensive institutions, and *FP-NII* to indicate for-profit, noninformation-intensive institutions. Finally, *Gender* is included in our analysis as a binary variable (1 = male, 0 = female), as previous research has shown a gender gap in compensation (e.g., England 1992). We also controlled for job level and modeled it as a set of binary variables with programmer as the base case, and *Project-Leader*, *Senior-Analyst*, and *Systems-Analyst* representing project leaders, senior systems analysts, and systems analysts, respectively.

3.3. Hierarchical Linear Models

We employed HLM (Bryk and Raudenbush 1992) for our analysis as HLM overcomes the statistical weaknesses of traditional methods for analyzing nested data (Hofmann 1997). Our hypotheses concerning the individual-, institution-, and cross-level determinants of compensation were examined using HLM in an incremental approach (Kreft and de Leeuw 1998). That is, we first specified a null model (Model 1), in which there were no individual- or institution-level predictors included. This enabled us to test whether there is significant variation in compensation, a necessary precondition for supporting our hypotheses. We then specified a model (Model 2), in which we added individual-level control variables, but included no other predictors. Subsequently, we added the individual-level predictors to this model (Model 3). This enabled us to evaluate our first set of hypotheses concerning the effects of individual-level determinants on compensation. Next, we specified a model (Model 4) in which we added institution-level predictors of the intercepts. This enabled us to evaluate our second set of hypotheses concerning the

[1] Although not the focus of our study, as a robustness check we added a term for experience squared to our models and re-estimated them. This is to control for a possible curvilinear relationship between experience and compensation as is done in the human capital literature. The results from this analysis do not change our findings.

Figure 1 Statistical Model



Notes. This figure is adapted from Kreft and DeLeeuw's depiction of multilevel models (1998, p. 72). In keeping with Kreft and DeLeeuw's approach, institution-level main effects are represented as institution-level determinants ($\gamma_{0\ 1\text{-}3}$) intersecting with the line between the constants (β_{0j}) and Compensation. Individual-level determinants are represented as each with its own line connecting the respective determinant ($\beta_{1\text{-}8\ j}$) and Compensation. Cross-level interactions are represented as institution-level determinants ($\gamma_{5\text{-}8\ 1\text{-}3}$) intersecting with the lines connecting the individual-level determinants ($\beta_{1\text{-}8\ j}$) and Compensation.

effects of institution-level determinants on compensation. Finally, we specified a full model (Model 5) in which we added institution-level predictors of the individual-level slopes. This enabled us to assess whether cross-level interactions provide significant incremental prediction of compensation (Hofmann and Gavin 1998). Following are the equations for our individual-, institution-, and cross-level models. Figure 1 illustrates our full model.

Individual-Level Model

$$\begin{aligned}\text{COMPENSATION}_{ij} &= \beta_{0j} + \beta_{1-3,j} * (\text{JOB}_{ij}) \\ &\quad + \beta_{4j} * (\text{GENDER}_{ij}) \\ &\quad + \beta_{5-7,j} * (\text{EDUCATION}_{ij}) \\ &\quad + \beta_{8j} * (\text{EXPERIENCE}_{ij}) + r_{ij}.\end{aligned}$$

Institution-Level Model

$$\begin{aligned}\beta_{0j} &= \gamma_{00} + \gamma_{01} * (\text{SIZE}_j) + \gamma_{02} * (\text{FP-II}_j) \\ &\quad + \gamma_{03} * (\text{FP-NII}_j) + u_{0j}, \\ \beta_{1-3,j} &= \gamma_{1-3,0} + u_{1-3,j}, \\ \beta_{4j} &= \gamma_{40} + u_{4j}, \\ \beta_{5-7,j} &= \gamma_{5-7,0} + \gamma_{5-7,1} * (\text{SIZE}_j) + \gamma_{5-7,2} * (\text{FP-II}_j) \\ &\quad + \gamma_{5-7,3} * (\text{FP-NII}_j) + u_{5-7,j}, \\ \beta_{8j} &= \gamma_{80} + \gamma_{81} * (\text{SIZE}_j) + \gamma_{82} * (\text{FP-II}_j) \\ &\quad + \gamma_{83} * (\text{FP-NII}_j) + u_{8j}.\end{aligned}$$

Cross-Level Model

$$\begin{aligned}&\text{COMPENSATION}_{ij} \\ &\quad = \gamma_{00} + \gamma_{01} * (\text{SIZE}_j) + \gamma_{02} * (\text{FP-II}_j) + \gamma_{03} * (\text{FP-NII}_j) \\ &\quad + (\gamma_{1-3,0}) * \text{JOB}_{ij} + (\gamma_{40}) * \text{GENDER}_{ij}\end{aligned}$$

$$+(\gamma_{5-7,0}+\gamma_{5-7,1}*(\text{SIZE}_j)+\gamma_{5-7,2}*(\text{FP-II}_j)$$
$$+\gamma_{5-7,3}*(\text{FP-NII}_j))*\text{EDUCATION}_{ij}$$
$$+(\gamma_{80}+\gamma_{81}*(\text{SIZE}_j)+\gamma_{82}*(\text{FP-II}_j)$$
$$+\gamma_{83}*(\text{FP-NII}_j))*\text{EXPERIENCE}_{ij}$$
$$+u_{0j}+u_{1-3j}*\text{JOB}_{ij}+u_{4j}*\text{GENDER}_{ij}$$
$$+u_{5-7j}*\text{EDUCATION}_{ij}+u_{8j}*\text{EXPERIENCE}_{ij}+r_{ij}.$$

Before estimating the models, we centered all of our individual- and institution-level variables using grand mean centering. Without centering, our data exhibit very high levels of multicollinearity, and grand mean centering reduces this collinearity substantially. In addition, grand mean centering is the most appropriate for assessing whether institution-level predictors provide incremental prediction of compensation over and above individual-level predictors (Hofmann and Gavin 1998, p. 634). With grand mean centering, the intercept at the individual level represents the expected value of compensation for an individual with average levels of the individual-level predictors. At the institution level, grand mean centering implies that the institution-level coefficients (i.e., for size, sector, and information intensity) represent the relationship between these institution-level predictors and compensation, less the influence of the individual-level predictors.[2]

4. Estimation and Results

We estimated our models using full maximum likelihood, empirical Bayes procedures, and the EM algorithm (Dempster et al. 1977) in HLM (Raudenbush et al. 2000).[3] We confirmed that the distributional assumptions were met and conducted a number of specification checks for the models. The Kolmogorov-Smirnov test for normality of residuals in large samples (Stephens 1986) supports the normality assumption at the 5% significance level for our base and total compensation models, after a log transformation of base compensation and total compensation. After grand mean centering, multicollinearity is low, as reflected in condition indices with values of less than 12 for the models. We tested the homogeneity of variance assumption using the H test statistic (Bryk and Raudenbush 1992), and values for this test statistic suggest no problems with heterogeneity. Using the criteria specified by Belsley et al. (1980), we identified six outliers in our base compensation model and five outliers in our total compensation model. However, the outliers do not have a significant impact, as our results from the models estimated without outliers are consistent with those when all observations are included. Therefore, we report our results with all observations included. Finally, we examined alternative specifications for our models, including fixed effects, random intercepts, and random coefficients. Our reported results are from the random coefficients specification for the models.[4]

[2] Without centering the data, the value of the condition index exceeds 214 in both base compensation and total compensation models. This is well above the recommended limit of 30 for this value (Belsley et al. 1980). With grand mean centering only at the individual level, the condition index at 74 still exceeds the recommended limit. After grand mean centering at both levels, the condition index falls below 30 in both base and total compensation models. Thus, to mitigate multicollinearity, we grand mean center both individual-level and institution-level variables. For cross-level interactions, in rare cases under grand mean centering there can be a potential confounding of the within-group slope and the between-group interaction. To determine whether cross-level interactions are affected by a potential confounding of within-group slope and between-group interaction, one can include institution means of the individual-level predictors as predictors of the institution intercept term, and use group mean centering when estimating the cross-level effects (Hofmann and Gavin 1998, pp. 631–632). We reestimated the cross level effects in our base and total compensation models using this approach. The results from this reestimation are consistent with those we obtain using grand mean centering. Thus, centering choice does not impact our results for the cross-level interactions.

[3] Empirical Bayes estimates are calculated for the randomly varying individual-level coefficients. Generalized least-squares (GLS) estimates are computed for coefficients of the fixed effects at both the individual- and institution- levels, and robust standard errors are used in determining the significance of these coefficients (robust standard errors are consistent even if the HLM assumptions are violated). The EM algorithm is used in an iterative manner to derive maximum likelihood estimates of the variance-covariance components for the residuals in the models.

[4] A fixed-effects specification is not appropriate for our analysis because it views differences between institutions as parametric shifts of the regression function, and the results cannot be

Table 1 Descriptive Statistics and Correlations

Variable	Mean (s.d.)	1	2	3	4	5	6	7	8	9	10	11	12	13
1. Base Compensation[a]	10.65 (0.38)	—												
2. Total Compensation[a]	10.76 (0.40)	0.97**	—											
3. Project Leader[d]	0.11 (0.32)	0.46**	0.47**	—										
4. Senior Analyst[d]	0.22 (0.42)	0.39**	0.38**	—	—									
5. Systems Analyst[d]	0.28 (0.45)	−0.03	−0.05	—	—	—								
6. Gender[c]	0.48 (0.50)	−0.07	−0.08	−0.02	−0.06	0.02	—							
7. Education1 (IT Grad)[b]	0.50 (0.50)	0.15*	0.12*	0.03	0.13*	0.05	0.04	—						
8. Education2 (Non-IT Grad)[b]	0.20 (0.40)	0.18*	0.19*	0.11*	0.05	0.10*	−0.01	—	—					
9. Education3 (IT non-Grad)[b]	0.20 (0.40)	−0.27**	−0.26**	−0.05	−0.09*	−0.13*	0.05	—	—	—				
10. IT Work Experience	7.03 (5.73)	0.57**	0.58**	0.32**	0.21**	−0.15*	−0.11*	−0.19*	0.03	0.28*	—			
11. FP-II(For-Profit-Info-Intensive)[e]	0.74 (0.44)	−0.04	−0.15	−0.01	0.02	0.08	0.09	0.16	−0.11	0.08	−0.12	—		
12. FP-NII (For-Profit-Noninfo-Intensive)[e]	0.49 (0.51)	0.08	0.13	0.08	−0.06	−0.06	−0.11	−0.10	0.11	−0.17	0.08	—	—	
13. Institution Size[a]	6.55 (1.51)	0.02	0.08	−0.03	0.16	−0.06	−0.02	−0.10	0.12	0.13	0.04	0.22	−0.32	—

Notes: $N = 1{,}576$ for evaluating pairwise correlations between individual-level variables or between individual- and institution-level variables; $N = 39$ for evaluating pairwise correlations between institution-level variables. Pearson product moment correlations are reported for pairs of continuous variables, Spearman rank correlations are reported for pairs of continuous and dichotomous variables, and Phi correlations are reported for pairs of dichotomous variables. [a]Base Compensation, Total Compensation, and Institution Size are reported using the natural logarithm transformation of these variables. [b]Coding: 0 = non-IT nongraduate; 1 = IT graduate (7); 1 = IT nongraduate (8); 1 = IT nongraduate (9). [c]Coding: 0 = female, 1 = male. [d]Coding: 0 = programmer, 1 = project leader (3); 1 = senior systems analyst (4); 1 = systems analyst (5). [e]Coding: 0 = not-for-profit, 1 = for-profit-info-intense (11), 1 = for-profit-non-info-intense (12). †; $p < 0.10$; *$p < 0.05$; **$p < 0.01$; ***$p < 0.001$.

Table 1 presents descriptive statistics and intercorrelations for all variables in our study. After evaluating distributional assumptions, we established that there is significant variation in compensation to be explained (Bryk and Raudenbush 1992). This was done using HLM to estimate a null model with only an intercept term included (see "Model 1" in Tables 2 and 3 for base compensation and total compensation, respectively). Tests indicate significant variance to be explained in base compensation ($\chi^2 = 197.51$, $df = 38$, $p < 0.01$) and in total compensation ($\chi^2 = 255.06$, $df = 38$, $p < 0.01$). Most of the variation in compensation is at the individual level: For base compensation, 88% of the variance is between individuals, and 12% is between institutions; while for total compensation, 85% of the variance is between individuals, and 15% is between institutions. We estimated Models 2 through 5 to evaluate the individual-, institution-, and cross-level determinants of compensation and calculated the proportion of variance explained from adding each set of determinants to the

generalized to cover other institutions not in the dataset. We estimated both random intercepts and random coefficients specifications. While the results are consistent across both specifications, the random coefficients model explains more variance in compensation, and chi-squared tests indicate that random effects are present for the individual-level variables. Thus, the random coefficients specification is most appropriate.

Table 2 Results of HLM Estimation for Base Compensation[a]

Variable (coefficient)	Base compensation				
	Model 1	Model 2	Model 3	Model 4	Model 5
Intercept (γ_{00})	**10.633***** (0.026)	**10.637***** (0.026)	**10.637***** (0.019)	**10.637***** (0.018)	**10.638***** (0.018)
PROJECT-LEADER (γ_{10})		**0.861***** (0.037)	**0.486***** (0.028)	**0.482***** (0.029)	**0.483***** (0.033)
SENIOR-ANALYST (γ_{20})		**0.574***** (0.030)	**0.350***** (0.025)	**0.346***** (0.025)	**0.340***** (0.029)
SYSTEMS-ANALYST (γ_{30})		**0.280***** (0.023)	**0.194***** (0.019)	**0.192***** (0.019)	**0.191***** (0.022)
GENDER (γ_{40})		**−0.013** (0.017)	**0.011** (0.011)	**0.012** (0.011)	**0.011** (0.011)
EDUCATION1 (IT-Grad) (γ_{50})			**0.276***** (0.039)	**0.277***** (0.039)	**0.233***** (0.041)
EDUCATION2 (Non-IT Grad) (γ_{60})			**0.291***** (0.036)	**0.291***** (0.036)	**0.246***** (0.037)
EDUCATION3 (IT-Non-Grad) (γ_{70})			**0.104***** (0.024)	**0.105***** (0.024)	**0.068*** (0.029)
EXPERIENCE (γ_{80})			**0.037***** (0.002)	**0.037***** (0.002)	**0.036***** (0.003)
INSTITUTION-SIZE[b] (γ_{01})				**0.003** (0.011)	**−0.003** (0.014)
FP-II (For-Profit-Info-Intensive) (γ_{02})				**0.043** (0.040)	**0.032** (0.050)
FP-NII (For-Profit-Noninfo-Intensive) (γ_{03})				**−0.059** (0.038)	**−0.047** (0.047)
EDUCATION1*INSTITUTION-SIZE (γ_{51})					**0.069**** (0.020)
EDUCATION1*FP-II (γ_{52})					**−0.150**** (0.055)
EDUCATION1*FP-NII (γ_{53})					**−0.352***** (0.058)
EDUCATION2*INSTITUTION-SIZE (γ_{61})					**0.069***** (0.017)
EDUCATION2*FP-II (γ_{62})					**−0.187***** (0.048)
EDUCATION2*FP-NII (γ_{63})					**−0.356***** (0.051)
EDUCATION3*INSTITUTION-SIZE (γ_{71})					**0.031*** (0.014)
EDUCATION3*FP-II (γ_{72})					**−0.096**** (0.032)
EDUCATION3*FP-NII (γ_{73})					**−0.255***** (0.030)
EXPERIENCE*INSTITUTION-SIZE (γ_{81})					**−0.001** (0.001)
EXPERIENCE*FP-II (γ_{82})					**−0.005**† (0.003)
EXPERIENCE*FP-NII (γ_{83})					**−0.009** (0.008)
Deviance (−2 log likelihood)	**1,328.752**	**−255.485**	**−1,524.188**	**−1,529.483**	**−1,560.007**
Deviance Difference (ΔDev)		**1,584.237*****	**1,268.703*****	**5.295**	**30.524****
Proportion of Variance Explained		**57.75%**	**75.41%**	**76.19%**	**80.45%**

Notes: $N = 1{,}576$ at individual level; $N = 39$ at institution level. Unstandardized coefficient estimates are reported with robust standard errors in parentheses; there are 38 *df* for evaluating the significance of estimated coefficients. *df* for evaluating deviance difference are 21, 34, 3, and 12, respectively. [a]The natural logarithm of Base Compensation is used. [b]The natural logarithm of Institution Size is used. $^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Table 3 Results of HLM Estimation for Total Compensation[a]

Variable	Total compensation Model 1	Model 2	Model 3	Model 4	Model 5
Intercept (γ_{00})	**10.739***** (0.030)	**10.742***** (0.031)	**10.741***** (0.026)	**10.740***** (0.026)	**10.743***** (0.025)
PROJECT-LEADER (γ_{10})		**0.884***** (0.036)	**0.537***** (0.023)	**0.535***** (0.025)	**0.520***** (0.031)
SENIOR-ANALYST (γ_{20})		**0.592***** (0.030)	**0.378***** (0.022)	**0.373***** (0.023)	**0.357***** (0.028)
SYSTEMS-ANALYST (γ_{30})		**0.291***** (0.023)	**0.205***** (0.019)	**0.204***** (0.019)	**0.199***** (0.022)
GENDER (γ_{40})		**−0.010** (0.017)	**0.010** (0.011)	**0.008** (0.011)	**0.007** (0.011)
EDUCATION1 (IT-Grad) (γ_{50})			**0.302***** (0.044)	**0.297***** (0.043)	**0.236***** (0.036)
EDUCATION2 (Non-IT Grad) (γ_{60})			**0.312***** (0.040)	**0.311***** (0.039)	**0.248***** (0.033)
EDUCATION3 (IT-Non-Grad) (γ_{70})			**0.122***** (0.026)	**0.118***** (0.026)	**0.067**** (0.026)
EXPERIENCE (γ_{80})			**0.035***** (0.002)	**0.035***** (0.002)	**0.035***** (0.003)
INSTITUTION-SIZE[b] (γ_{01})				**0.018** (0.011)	**−0.002** (0.017)
FP-II (For-Profit-Info-Intensive) (γ_{02})				**0.034** (0.026)	**0.060** (0.061)
FP-NII (For-Profit-Noninfo-Intensive) (γ_{03})				**−0.058** (0.039)	**−0.023** (0.071)
EDUCATION1*INSTITUTION-SIZE (γ_{51})					**0.072***** (0.018)
EDUCATION1*FP-II (γ_{52})					**−0.134**** (0.048)
EDUCATION1*FP-NII (γ_{53})					**−0.331***** (0.050)
EDUCATION2*INSTITUTION-SIZE (γ_{61})					**0.068***** (0.016)
EDUCATION2*FP-II (γ_{62})					**−0.177***** (0.038)
EDUCATION2*FP-NII (γ_{63})					**−0.359***** (0.035)
EDUCATION3*INSTITUTION-SIZE (γ_{71})					**0.032**** (0.014)
EDUCATION3*FP-II (γ_{72})					**−0.101**** (0.038)
EDUCATION3*FP-NII (γ_{73})					**−0.263***** (0.035)
EXPERIENCE*INSTITUTION-SIZE (γ_{81})					**0.002**[†] (0.001)
EXPERIENCE*FP-II (γ_{82})					**−0.002** (0.003)
EXPERIENCE*FP-NII (γ_{83})					**−0.010**[†] (0.005)
Deviance (−2 log likelihood)	**1,438.983**	**−137.357**	**−1,342.696**	**−1,346.255**	**−1,373.385**
Deviance Difference (Δ Dev)		**1,576.340*****	**1,205.339*****	**3.559**	**27.130****
Proportion of Variance Explained		**55.53%**	**71.98%**	**72.28%**	**74.86%**

Notes: $N = 1{,}576$ at individual level; $N = 39$ at institution level. Unstandardized coefficient estimates are reported with robust standard errors in parentheses. There are 38 *df* for evaluating the significance of estimated coefficients. *df* for evaluating deviance difference are 21, 34, 3, and 12, respectively. [a]The natural logarithm of Total Compensation is used. [b]The natural logarithm of Institution Size is used. $^{\dagger}p < 0.10$; $^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

models (Bryk and Raudenbush 1992). The significance of the incremental variance explained is assessed by examining the differences between the deviance statistics (Δdev) for each pair of nested models in a manner analogous to assessing the change in R^2 in traditional hierarchical regression analysis.[5] We then conducted a series of hypothesis tests to examine our results in light of our hypotheses. Tables 2 and 3 show the detailed results from the estimation of the different models, and Table 4 summarizes results from our hypothesis testing. In the following sections, we discuss our results.

4.1. Results: Human Capital Determinants

Our first set of hypotheses (H1a and H1b) posited a positive relationship between human capital endowments and compensation. These hypotheses are supported in that both education and experience explain significant incremental variance in base (Δdev = 1,268.70, $df = 34$, $p < 0.001$) and total compensation (Δdev = 1,205.34, $df = 34$, $p < 0.001$). In terms of education, individuals with a bachelor's degree are paid more than those with an associate's degree in base ($\chi^2 = 57.44$, $df = 1$, $p < 0.001$) and total compensation ($\chi^2 = 55.88$, $df = 1$, $p < 0.001$); while IT majors are paid more than non-IT majors in both base ($\chi^2 = 7.86$, $df = 1$, $p < 0.01$) and total compensation ($\chi^2 = 11.23$, $df = 1$, $p < 0.01$). In terms of experience, IT professionals with more experience receive significantly more base ($t = 15.55$, $df = 38$, $p < 0.001$) and total compensation ($t = 17.28$, $df = 38$, $p < 0.001$) than those with less experience.

4.2. Results: Institutional Determinants

Hypotheses 2a, 2b, and 2c specified significant and positive main effects of institution size, sector, and information intensity on compensation. These hypotheses are not supported. The deviance differences shown at the bottom of the columns labeled "Model 4" in Tables 2 and 3 indicate that the institution-level variables do not significantly explain incremental variation in compensation, in addition to that explained already by the individual-level control and predictor variables in the models (base compensation: Δdev = 5.29, $df = 3$, $p > 0.10$; total compensation: Δdev = 3.56, $df = 3$, $p > 0.10$).[6] As shown in Tables 2 and 3, the coefficient for institution size is not statistically significant for base ($t = 1.48$, $df = 35$, $p > 0.10$) and total compensation ($t = 1.68$, $df = 35$, $p > 0.10$). As shown in Table 4, a joint test of the coefficients for for-profit institutions versus not-for-profit institutions indicates no difference in compensation (base compensation: $\chi^2 = 3.06$, $df = 2$, $p > 0.05$; total compensation: $\chi^2 = 4.78$, $df = 2$, $p > 0.05$). Also, a joint test comparing the coefficients for information-intensive versus noninformation-intensive institutions shows no difference in compensation (base compensation: $\chi^2 = 0.05$, $df = 1$, $p > 0.50$; total compensation: $\chi^2 = 0.13$, $df = 1$, $p > 0.50$).

4.3. Results: Cross-Level Human Capital × Institutional Determinants

We had hypothesized cross-level interactions between individual and organizational variables on compensation. As shown at the bottom of the columns labeled "Model 5" in Tables 2 and 3, our full models explain 80.45% of the variance in base compensation and 74.86% of the variance in total compensation. The cross-level interactions explain significant incremental variance in base and total compensation in addition to that already explained by the individual- and institution-level variables in the models (base compensation: Δdev = 30.52, $df = 12$, $p < 0.01$; total compensation: Δdev = 27.13, $df = 12$, $p < 0.01$). As shown in Table 4, there are significant cross-level

[5] The deviance statistic is twice the negative log-likelihood, where the log-likelihood is the value of the likelihood associated with the maximum likelihood estimates under a particular model. Differences in deviances have a chi-square distribution and show, compared to the degrees of freedom lost, whether the alternative model is a significant improvement over the original model (Kreft and de Leeuw 1998).

[6] Note that, for our data, it does not matter in terms of statistical significance whether we add the institution-level variables before or after adding the individual-level variables. If the institution-level variables are entered before the individual-level variables, they still do not explain significant variance in compensation (base compensation: Δdev = 4.25, $df = 3$, $p > 0.10$; total compensation: Δdev = 4.07, $df = 3$, $p > 0.10$).

Table 4 Results of Hypothesis Testing

Hypothesis	Test	Base compensation model	Total compensation model	Interpretation
1a Education	$\gamma_{50}+\gamma_{60}-\gamma_{70}=0$	$\chi^2=57.442, df=1, p<0.001$	$\chi^2=55.880, df=1, p<0.001$	Bachelor's degree holders paid more than associate's degree holders
	$\gamma_{50}+\gamma_{70}-\gamma_{60}=0$	$\chi^2=7.857, df=1, p<0.01$	$\chi^2=11.228, df=1, p<0.01$	IT majors paid more than non-IT majors
1b Experience	$\gamma_{80}=0$	$t=15.553, df=38, p<0.001$	$t=17.276, df=38, p<0.001$	More experienced paid more than less experienced
2a Institution size	$\gamma_{01}=0$	$t=0.293, df=35, p>0.05$	$t=1.683, df=35, p>0.05$	No difference in average compensation in large vs. small institutions
2b For-profit vs. Not-for-profit institutions	$\gamma_{02}+\gamma_{03}=0$	$\chi^2=3.062, df=2, p>0.05$	$\chi^2=4.738, df=2, p>0.05$	No difference in average compensation in FP vs. NFP institutions
2c Info-Intensive vs. non-info-intensive institutions	$\gamma_{02}-\gamma_{03}=0$	$\chi^2=0.046, df=1, p>0.50$	$\chi^2=0.132, df=1, p>0.50$	No difference in average compensation in II vs. NII institutions
3a Institution size*education	$\gamma_{51}+\gamma_{61}-\gamma_{71}=0$	$\chi^2=11.533, df=1, p<0.001$	$\chi^2=14.588, df=1, p<0.001$	Bachelor's degree holders paid more in large vs. small institutions
	$\gamma_{51}+\gamma_{71}-\gamma_{61}=0$			Associate's degree holders paid more in small vs. large institutions
		$\chi^2=2.115, df=1, p>0.05$	$\chi^2=2.616, df=1, p>0.05$	No difference in compensation for IT majors vs. non-IT majors in large vs. small Institutions
3b Institution size*experience	$\gamma_{81}=0$	$t=1.117, df=35, p>0.05$	$t=1.338, df=35, p>0.05$	No difference in compensation for experience in large vs. small Institutions
4a For-profit vs. not-for-profit institutions*education	$\gamma_{52}+\gamma_{53}+\gamma_{62}+\gamma_{63}-\gamma_{72}-\gamma_{73}=0$	$\chi^2=16.206, df=2, p<0.05$	$\chi^2=19.529, df=2, p<0.05$	Associate's degree holders paid more in FP than in NFP institutions
	$\gamma_{52}+\gamma_{53}+\gamma_{72}+\gamma_{73}-\gamma_{62}-\gamma_{63}=0$	$\chi^2=12.051, df=2, p<0.05$	$\chi^2=9.539, df=2, p<0.05$	Non-IT majors paid more in FP than NFP institutions
4b For-profit vs. Not-for-profit institutions* experience	$\gamma_{82}+\gamma_{83}=0$	$\chi^2=4.122, df=2, p>0.05$	$\chi^2=5.457, df=2, p>0.05$	No difference in compensation for experience in FP vs. NFP institutions
5a Info-intensive vs. Non-info-intensive institutions*education	$\gamma_{52}+\gamma_{62}-\gamma_{72}-\gamma_{53}-\gamma_{63}+\gamma_{73}=0$	$\chi^2=6.268, df=2, p<0.05$	$\chi^2=6.184, df=2, p<0.05$	Bachelor's degree holders paid more in II than in NII institutions
	$\gamma_{52}+\gamma_{72}-\gamma_{62}-\gamma_{53}-\gamma_{73}+\gamma_{63}=0$	$\chi^2=8.229, df=2, p<0.05$	$\chi^2=6.437, df=2, p<0.05$	IT majors paid more in II than in NII institutions
5b Info-intensive vs. Non-info-intensive institutions*experience	$\gamma_{82}-\gamma_{83}=0$	$\chi^2=3.058, df=1, p>0.05$	$\chi^2=2.999, df=1, p>0.05$	No difference in compensation for experience in II vs. NII institutions

interactions between institution size, sector, information intensity, and education on compensation, providing support for Hypotheses 3a, 4a, and 5a. Joint hypothesis tests of the cross-level coefficients for education and institution size indicate that those with a bachelor's degree are paid differently in large versus small institutions (base compensation: $\chi^2 = 11.53$, $df = 1$, $p < 0.001$; total compensation: $\chi^2 = 14.59$, $df = 1$, $p < 0.001$); however, there is no difference in compensation for IT majors in large versus small institutions (base compensation: $\chi^2 = 2.12$, $df = 1$, $p > 0.05$; total compensation: $\chi^2 = 2.62$, $df = 1$, $p > 0.05$). Joint tests of the cross-level coefficients for sector and education indicate that Bachelor's degree holders and IT majors are paid differently in not-for-profit institutions than in for-profit institutions (base compensation: $\chi^2 = 16.21$, $df = 2$, $p < 0.05$, and $\chi^2 = 12.05$, $df = 2$, $p < 0.05$, respectively; total compensation: $\chi^2 = 19.53$, $df = 2$, $p < 0.05$, and $\chi^2 = 9.54$, $df = 2$, $p < 0.05$, respectively). Further, bachelor's degree holders and IT majors are paid differently in information-intensive institutions than in noninformation-intensive institutions (base compensation: $\chi^2 = 6.27$, $df = 2$, $p < 0.05$, and $\chi^2 = 8.23$, $df = 2$, $p < 0.05$, respectively; total compensation: $\chi^2 = 6.18$, $df = 2$, $p < 0.05$, and $\chi^2 = 6.44$, $df = 2$, $p < 0.05$, respectively). The coefficients for the cross-level interactions of experience with institution size, sector, and information intensity on compensation are not statistically significant. Thus, Hypotheses 3b, 4b, and 5b are not supported. We discuss and interpret these results in the next section.

5. Discussion

Our empirical analysis confirms many of our hypotheses but also reveals some surprising findings. First, consistent with Hypotheses 1a and 1b, we find that compensation of IT professionals is positively related to human capital endowments of education and work experience. Second, contrary to our expectations in Hypotheses 2a to 2c, we find that institutional factors such as size, sector, and information intensity do not significantly affect IT compensation. We believe these nonsignificant findings can be attributed to the severe imbalance of IT labor supply and demand. When labor supply exceeds demand, institutions possess relatively greater bargaining power vis-à-vis workers and can exercise differentiating compensation strategies to attract and retain workers, resulting in institutional effects on compensation. However, under severe labor shortages, workers possess greater bargaining power because they enjoy plentiful jobs, while institutions have to bid for IT professionals from a very restricted pool of IT talent. As a result, institutions do not possess as much discretion as they typically would have to differentiate in their compensation strategies (Ehrenberg and Smith 1997).

Finally, for our cross-level Hypotheses 3a to 5b, our analyses revealed four interesting patterns of results. First, as shown in Figures 2a and 2b, large institutions pay more than small institutions to bachelor's degree holders; however, small institutions surprisingly pay more than large institutions to associate's degree holders. As suggested by Reder (1955), small institutions are in general less attractive as employers because of perceived fewer growth opportunities. In the context of IT work, small institutions could be less appealing to IT professionals because small, unlike large, institutions, do not have large IT departments to invest in IT talent. Thus, small institutions could be forced to offer better compensation to attract even associate's degree holders to the institution.

Second, as shown in Figures 2c and 2d, for-profits compensate more than not-for-profits to associate's degree holders and non-IT majors. This is consistent with the institutional rigidity arguments put forth earlier in the paper. According to Hallock (2000), not-for-profits often peg compensation to educational credentials. Thus, unlike for-profits, not-for-profits cannot easily relax institutional constraints that tie compensation to educational qualifications. While a not-for-profit institution may wish to recognize the market value of an IT professional, it is often unable to do so without disrupting the compensation strategies for professionals with similar internal value in other departments within the institution. As a result, not-for-profits are more constrained than for-profits in their ability to adjust compensation strategies in a dynamic labor market. In contrast, for-profits can adjust compensation upward for associate's degree

Figure 2a **Interactions Between Individual Education and Institutional Size on Base Compensation**

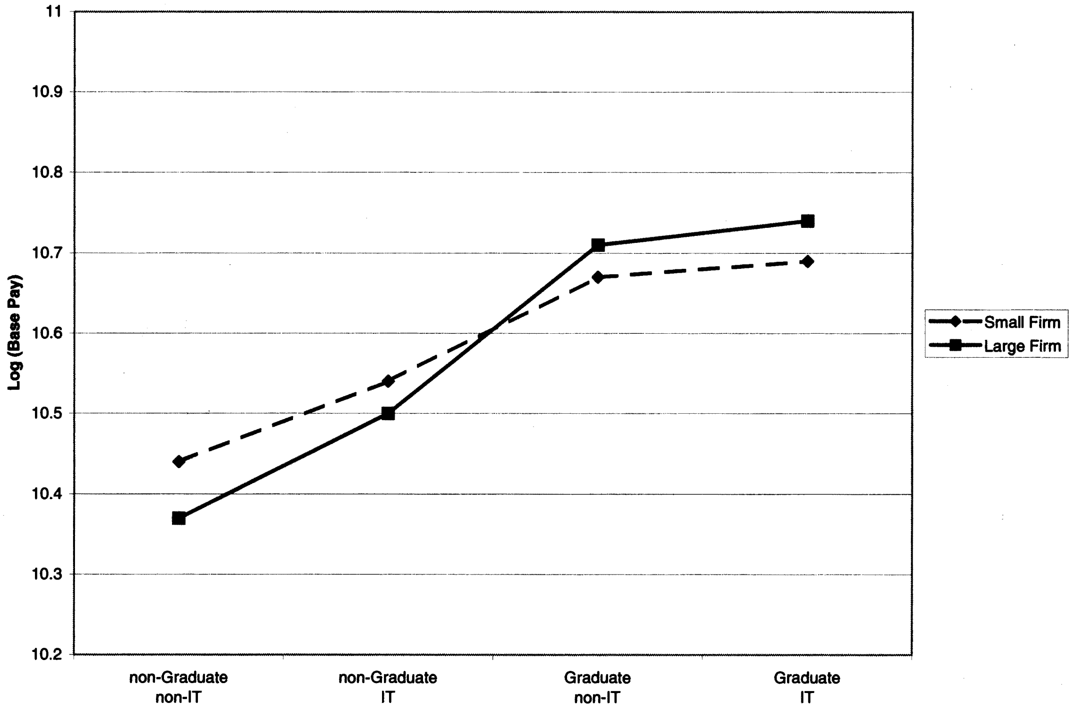


Figure 2b **Interactions Between Individual Education and Institutional Size on Total Compensation**

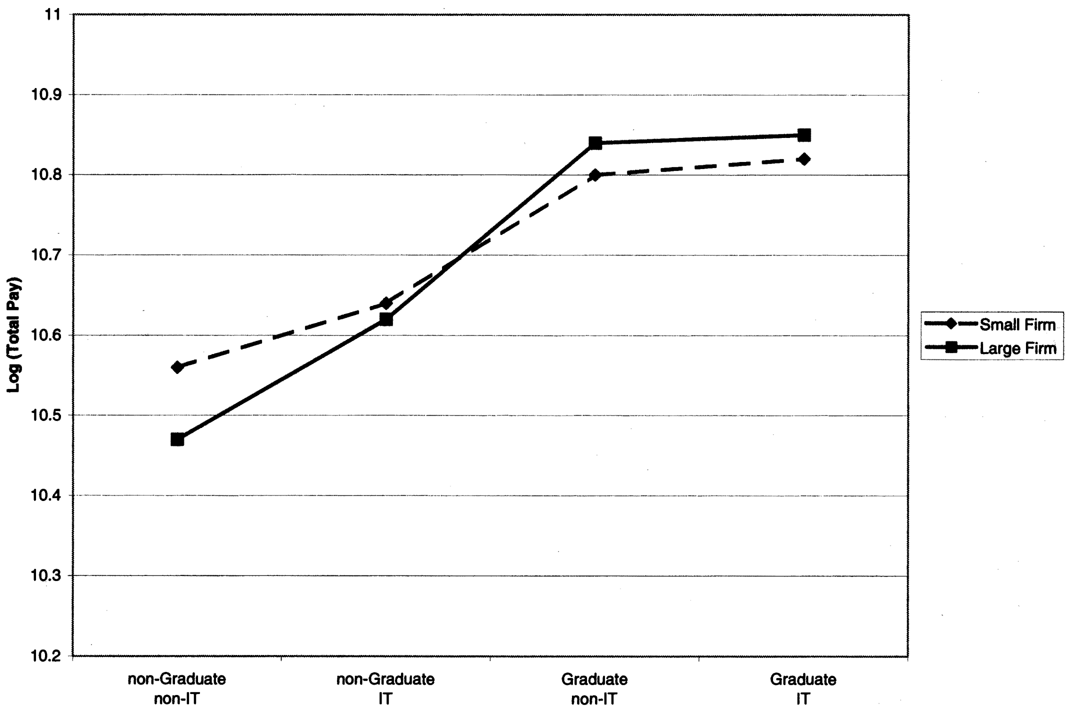


Figure 2c **Interactions Between Individual Education and Institutional Sector on Base Compensation**

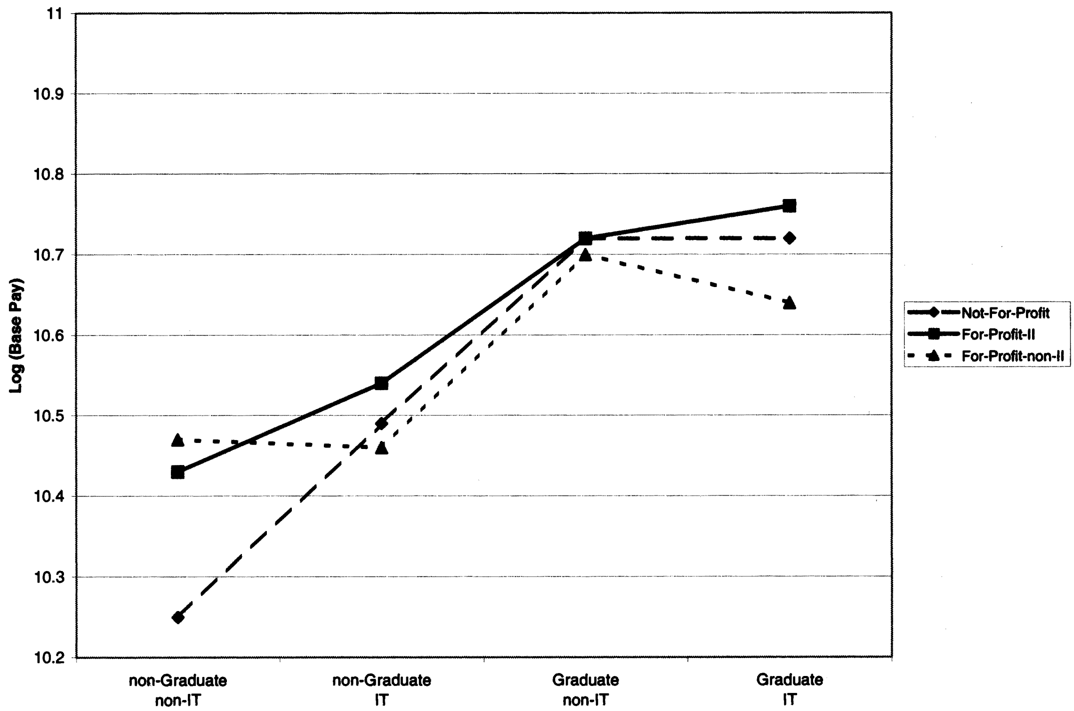
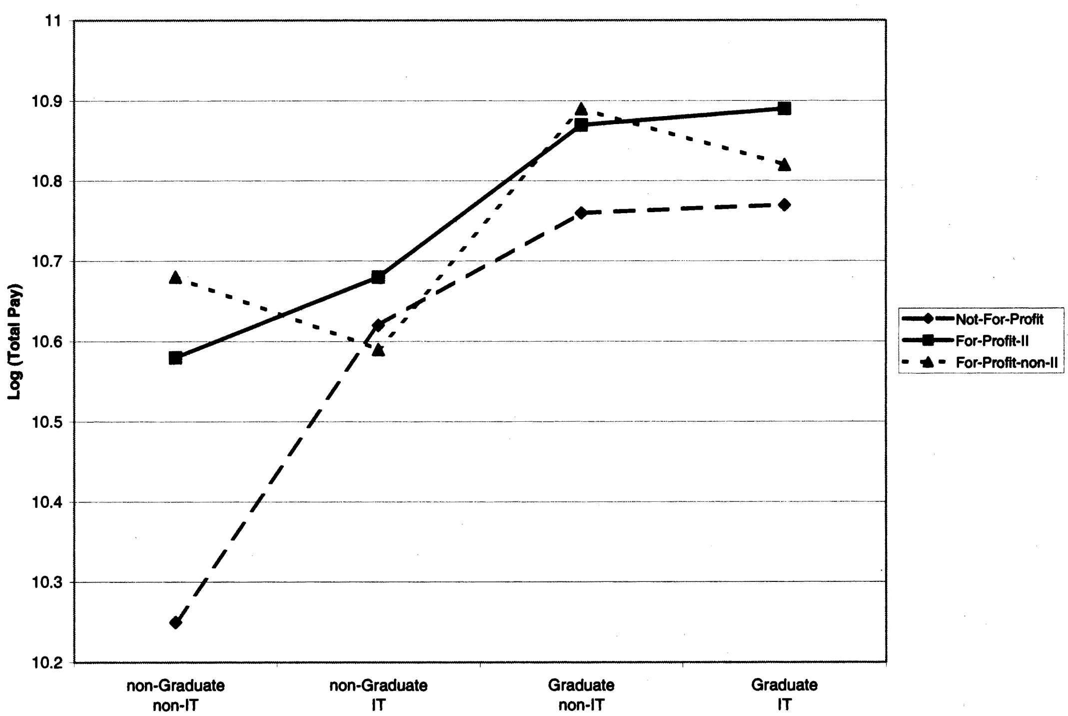


Figure 2d **Interactions Between Individual Education and Institutional Sector on Total Compensation**



holders and non-IT majors so as to attract and retain sufficient IT talent.

Third, also as depicted in Figures 2c and 2d, information-intensive institutions pay more than noninformation-intensive institutions to bachelor's degree holders and IT majors. This is consistent with our hypothesis. Because IT is the core competence in information-intensive institutions, it is paramount that these institutions attract and retain IT workers of high caliber, hence the findings.

Fourth and finally, contrary to our expectations, we find that experience interacts with neither institution size, nor sector, nor information intensity in predicting individual compensation. Institutions appear to value experience in the same way when making compensation decisions, even in a labor market characterized by overdemand and a highly mobile IT work force. This could reflect the importance of experience as an indicator of the ability of an individual to perform immediately in IT work. As research on work experience shows, skill-based competencies such as IT skills are action oriented, and by their nature, acquired through learning by doing (Tesluk and Jacobs 1998). Although conceptual principles and knowledge are important in IT work, skill-based competencies required for job performance are acquired primarily through practical work experience (Argyris 1993). Thus, our results imply that institutions reward experience similarly and are unwilling to compensate potentially incompetent IT professionals who lack practical work experience and may not be able to perform on the job or on demand.

6. Conclusions

Our study contributes to knowledge in two key ways. First, to the best of our knowledge, this study represents the first comprehensive and in-depth analysis of compensation for IT technical professionals. In this study, we complement the research on IT executive compensation by Anderson et al. (2000) and Talmor and Wallace (1998) by focusing on nonmanagerial IT professionals. Second, and more importantly, our study enriches existing theories of compensation by hypothesizing and testing cross-level determinants of compensation. Prior studies on compensation have largely focused on compensation strategies at a single level of analysis at a time. Our study reveals the importance of theorizing and modeling cross-level interactions. If cross-level interactions were not included, we would have underspecified the compensation models and failed to observe moderating effects of institutional characteristics on compensation. Based on the findings of this study and consistent with the recent development of methodologies for multi- and cross-level theorizing in the organization sciences (e.g., Klein and Kozlowski 2000), we encourage further research in IT to theorize and evaluate multi- and cross-level compensation models.

As for future research, studies could model noncash forms of IT compensation. We have focused on cash-based compensation strategies because the institutions in our sample do not offer other incentives (such as stock options) to their IT professionals. As stock options become more popular, it would be instructive to examine compensation strategies that embrace stock compensation and its varieties of share options. Future research should also explore the effects of other human capital attributes (e.g., technical skills or managerial competencies) and institutional factors (e.g., IT vendors versus client institutions) in determining compensation.

In terms of the IT labor market context, this study was conducted in Singapore where there are shortages of qualified IT professionals. We would expect the labor market imbalance and the corresponding lowered bargaining power of employers vis-à-vis IT professionals to hold in other nations where there is an IT labor shortage. Although the IT labor market context may be similar in other settings, the institutional context could be different. This is especially true about the institutional rules and regulations constraining personnel policies in the not-for-profit sector. As shown from the findings in this study, not-for-profit institutions enforce a compensation differential policy between bachelor's and associate's degree holders, despite labor shortages in IT. Obviously, such findings must be validated in other settings, and extension of our ideas to other institutional contexts is essential.

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