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Turnover or Turnaway? Competing Risks Analysis of Male and Female IT Professionals' Job Mobility and Relative Pay Gap

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This study draws on distributive justice, human capital, and stigmatization theories to hypothesize relationships between relative pay gap and patterns of job mobility. Our study also expands the criterion space of job mobility by contrasting different job destinations when information technology (IT) professionals make job moves. We examine three job moves: (a) turnover to another IT job in a different firm, (b) turnaway-within to a non-IT job, and (c) turnaway-between to a different firm and a non-IT job. We analyze work histories spanning 28 years for 359 IT professionals drawn from the National Longitudinal Survey of Youth. We report three major findings. First, as hypothesized, larger relative pay gaps significantly increase the likelihood of job mobility. Second, IT males and IT females have different job mobility patterns. IT males are more likely to turn over than turn away-between when faced with a relative pay gap. Further, and contrary to predictions from human capital theory, IT males are more likely to turn away-within than turn over. This surprising finding suggests that the ubiquitous use of IT in other business functions may have increased the value of IT skills for non-IT jobs and reduced the friction of moving from IT to other non-IT positions. Third, and consistent with stigmatization arguments, IT females are more likely to turn away from IT than to turn over when faced with a relative pay gap. In fact, to reduce relative pay gaps, IT females tend to take on lower-status jobs that pay less than their IT jobs. We conclude this study with important theoretical, practical, and policy implications.

Keywords: information technology professionals; relative pay gap; turnover; turnaway; job mobility; stigmatization; human capital; survival analysis; competing risks; longitudinal
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Introduction

The information technology (IT) profession continues to grapple with a severe imbalance of IT labor. In terms of demand, IT remains a fast-growing occupation in the United States, with an expected growth of 18% between 2012 and 2022 (Richards and Terkanian 2013). Yet, in terms of supply, the number of IT professionals in the United States has decreased sharply (National Science Board 2014). According to the National Science Foundation's *Science and Engineering Indicators 2014*, the number of bachelor's degrees in computer science reached a peak of 60,000 in 2004. But since then it has declined each year, and by 2011 the number dropped below 44,000. Computer science is the only scientific discipline with a downward trend in the number of undergraduate degrees (National Science Board 2014).[1] In addition, those already in the IT profession are prone to leave it. One study showed that as many as two-thirds of IT professionals tend to leave the IT profession (Joseph et al. 2007).

The imbalance of IT labor is further exacerbated by the lack of females in the industry (Trauth et al. 2009). From 2000 to 2009, interest in computer science among first-year undergraduate women had declined by 79% in 2009 (Ashcraft and Blithe 2009). In addition, the proportion of females in the U.S. IT workforce declined from 40% in 1989 (Information Technology

[1] Bachelor's degree holders in mathematics, biological sciences, engineering, physical sciences, and social sciences have all increased in number each year from 2000 to 2009 (National Science Board 2014).

Association of America 2005) to 26% in 2013 (Bureau of Labor Statistics 2013a).

To attract and retain IT talent, firms use pay as one of their main strategies (Morello 2012). But pay is also a powerful impetus for job mobility. Research suggests that absolute pay matters less in decisions to leave jobs compared to relative pay (Gerhart and Rynes 2003). A relative pay gap refers to the gap in one's pay compared to the pay received by comparable others (Galizzi and Lang 1998, Gupta et al. 2006, Schumacher 1997). Distributive justice theory suggests that when pay received is lower than pay of comparable others in similar jobs (i.e., a situation of inequity), action will be taken to restore this inequity (Colquitt 2008). This action, typically, is leaving one's job (Younts and Mueller 2001).

Empirical evidence supports the predictions of distributive justice. For example, field studies of U.S. manufacturing workers (Levine 1993), Italian automotive industry workers (Galizzi 2001, Galizzi and Lang 1998), and German blue-collar workers (Pfeifer and Schneck 2012) all report a positive relationship between relative pay and voluntary quits, controlling for the level of pay.

Although extant research has examined why individuals leave their jobs, it has been silent about the job *destinations* of workers who leave their current jobs. Joseph et al. (2012) discovered that job mobility is complex when one views the phenomenon less as a binary construct of staying or leaving a job and more as taking on another job (i.e., the destination). Job destinations are more complex as a construct because they are defined by two kinds of boundaries associated with job mobility: organizational and occupational.

Exploring an enriched criterion space for job mobility is important for refining theories of job mobility because it acknowledges that not all forms of job mobility, as a phenomenon, are binary in nature (Direnzo and Greenhaus 2011); that is, when individuals leave their jobs, they may cross organizational, occupational, or both boundaries (Joseph et al. 2012). Accordingly, we would expect different nomological networks (Cronbach 1958) for different types of job mobility in which the factors associated with job mobility within an occupation may differ from those associated with job mobility across occupations (McDuff and Mueller 2000).

In the context of our study, an enriched criterion facilitates understanding about whether a relative pay gap retains or pushes IT professionals out of firms and/or professions. In essence, this study examines patterns of IT professionals' job mobility associated with relative pay gap. In the next sections, we draw on distributive justice, human capital, and stigmatization theories to hypothesize relationships between relative pay gap and job moves by IT professionals.

Table 1 Job Mobility Destinations for IT Professionals

	Occupation	
	No change	Change
Firm		
No change	Stay (Cell 1)	Turnaway-within (Cell 3)
Change	Turnover (Cell 2)	Turnaway-between (Cell 4)

Theory and Hypotheses Development

The taxonomy of Joseph et al. (2012) (Table 1) differentiates job mobility by changes in firm (or employer or organization) and/or occupation (i.e., the IT profession in this case).

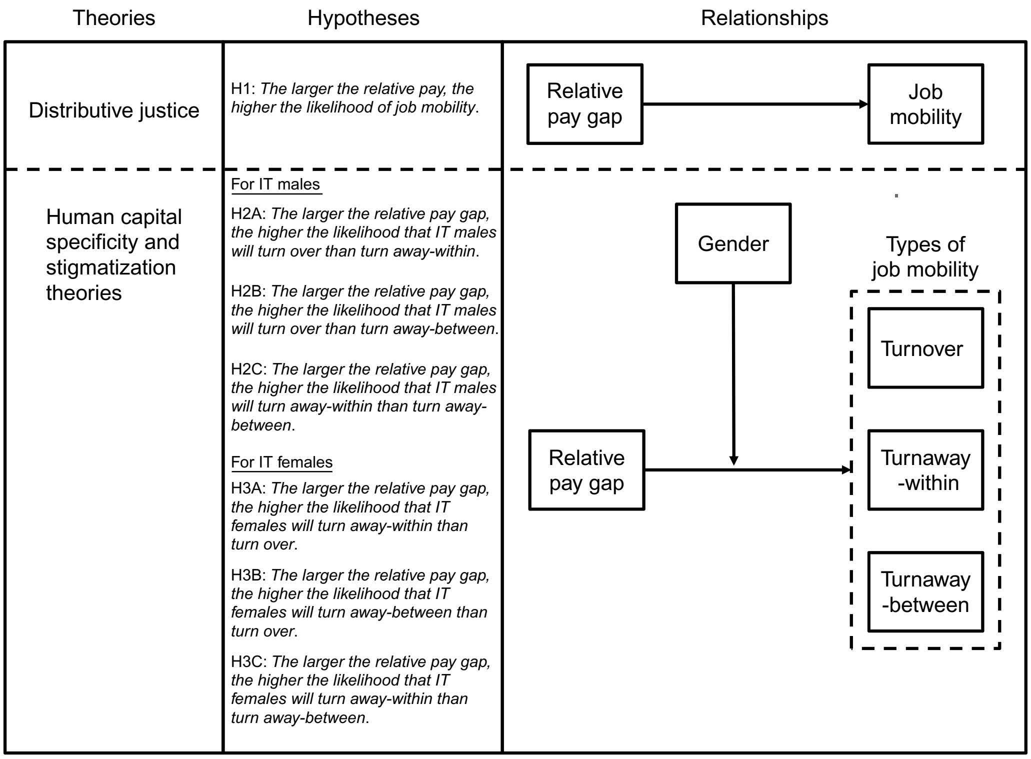
For *Stay* (Cell 1 in Table 1), there are no changes in either firm or occupation. For the purposes here, *Stay* is defined as remaining in an IT job in the current firm and in the IT profession. *Turnover* (Cell 2) involves a change in firm but not occupation. *Turnover*, therefore, is defined as voluntarily leaving an IT job for an alternative IT job with a different employer. *Turnaway-within* (Cell 3) involves no change in firm, but a change of occupation. *Turnaway-within* is defined as voluntarily leaving an IT job for a non-IT job within the current firm. Finally, *Turnaway-between* (Cell 4) involves a change of both firm and occupation. *Turnaway-between* is defined as voluntarily leaving an IT job for a non-IT job with a different firm.

Figure 1 provides an overview of the theories, hypotheses, and relationships in this study. First, we hypothesize relative pay gap and job mobility using tenets of distributive justice theory (Hypothesis 1). Then, we draw on human capital and stigmatization theories to distinguish different patterns of job mobility (turnover, turnaway-within, and turnaway-between) for IT males (Hypotheses 2A–2C) and IT females (Hypotheses 3A–3C).

Distributive Justice

Distributive justice reflects the fairness in the allocation of rewards (Colquitt 2008). Distributive justice theory suggests that an unfair allocation of rewards for similar work conducted under similar conditions creates a sense of distress. This distress prompts an action to restore fairness (Greenberg 1987). Through the lens of distributive justice theory, a relative pay gap reflects an unfair allocation of pay for similar work conducted under comparable conditions (Gerhart and Rynes 2003). Hence, a relative pay gap is likely to prompt an action to restore fairness. Prior empirical research offers evidence that job mobility is one action that restores such fairness (Tekleab et al. 2005). A worker restores fairness in pay by leaving her current job for another where pay is commensurate with market rates (Galizzi and Lang 1998,

Figure 1 Overview of the Theoretical Foundation, Hypotheses, and Relationships



Note. We thank a reviewer for suggesting this figure.

Schumacher 1997). Hence, as a baseline hypothesis, we expect the following:

Hypothesis 1. *The larger the relative pay gap, the higher the likelihood of job mobility.*

Human Capital Specificity and Stigmatization

Although distributive justice theory provides an established explanation for the above hypothesis, it is silent about explaining relative pay's relationship to various job destinations. This silence offers the opportunity to further refine our understanding of the link between relative pay gap and job mobility. We draw on human capital theory (Becker 1975, Sturman et al. 2008) to justify our hypotheses that associate relative pay gap with different forms of job mobility patterns, and on stigmatization theory (Crocker et al. 1998, Major and O'Brien 2005) to address gender differences in job mobility patterns.

Human Capital Specificity. Human capital theory distinguishes between general and specific human capital (Becker 1975, Sturman et al. 2008). General human capital includes skills that are easily transferable across domains, whereas specific human capital refers to skills that are unique and specialized to a particular domain, such as a firm or occupation. The uniqueness and transferability of specific human capital has cost-related implications for job mobility.

Recent research has identified two kinds of specific human capital held by IT professionals, i.e., firm-specific and IT-specific human capital (Mithas and Krishnan 2008, Slaughter et al. 2007). Firm-specific human capital is unique to a firm and less readily transferable to other firms (Slaughter et al. 2007). Firms tend to bear a significant portion of the costs associated with an employee's development of firm-specific human capital (Carless and Arnup 2011). To recoup investments and retain human capital within the firm, firms pay less in the earlier period in exchange for higher pay in a later period (Carless and Arnup 2011). Investments in firm-specific competencies tend to deter mobility across organizational boundaries because workers incur a cost by foregoing returns to their firm-specific human capital when they leave the firm.

IT-specific human capital is unique to IT jobs and less readily transferable to other occupations (Slaughter et al. 2007). Investments in occupation-specific human capital begin during formal occupational education in school and continue on the job (Carless and Arnup 2011). Moreover, IT-specific human capital requires continued investments because it is subject to professional obsolescence (Joseph et al. 2010, 2011). Investments in formal occupational education and continual professional development are often funded by workers and are not readily recouped by leaving the occupation (Maxwell 1987). IT professionals may be able to reap returns to their IT-specific human capital as long as they remain within the IT profession (Joseph et al. 2012). Investments in occupation-specific competencies tend to deter mobility across occupational boundaries because workers incur a cost by foregoing returns to their occupation-specific human capital when they leave their occupations.

From the human capital specificity point of view, we expect that IT professionals would turn over (find another IT job in another firm) rather than leave the profession to redress the relative pay gap, because turnover is the least costly strategy of job mobility. IT skills are valuable and transferable to IT jobs across firms because of the standardization of IT (Slaughter et al. 2007). The standardization of IT reduces training costs for firms when they purchase IT-specific human capital from the external labor market. Firms may pass part of the savings in training costs to IT professionals as higher pay (Mithas and Krishnan 2008), thereby narrowing a relative pay gap. As such, to redress a relative pay gap, IT professionals may be enticed to turn over rather than to turn away-within or turn away-between.

In comparing the likelihood of turnaway-within and turnaway-between, we expect, from a human capital specificity standpoint, that turnaway-within is more likely than turnaway-between to be the next likely mobility to redress relative pay gaps. Turnaway-within is the "seeding the line" strategy first reported by Reich and Kaarst-Brown (1999). The ubiquity of information technologies in line functions requires incumbents in these line functions to possess IT skills. By seeding the line, IT professionals move laterally into non-IT line jobs so that firms are able to reap the benefits of both their IT-specific and firm-specific human capital. Furthermore, firms would invest additionally to train these IT professionals in their new occupations within the firm (Kambourov and Manovskii 2009) and pay these professionals for their unique mix of IT-, line-, and firm-specific human capital.

Turnaway-between is expected to be the least likely form of job mobility. From a human capital perspective, turnaway-between discounts the value of both firm- and IT-specific human capital. Leaving both the firm and profession requires individuals to "start from scratch" and rely on general human capital (Kambourov and Manovskii 2009). General human capital tends to be more available in the labor market and, as a result, is less valuable to firms compared to specific human capital (Møen 2005). As such, returns to general human capital should be lower compared to returns to specific human capital (Gathmann and Schonberg 2010).

Given higher individual investments in IT skills and the prospect of deferred returns to firm-specific competencies, the costs associated with turnover are likely to be lower compared with costs associated with turnaway-within and -between firms. Hence, based on human capital arguments, we would expect the relative pay gap to be more strongly associated with turnover than with turnaway-within or turnaway-between. However, this expectation is based on the premise that all IT professionals are treated equally. That may not be the case for IT females. As we describe in the following section, females suffer from a stigmatization in the IT profession, and as such we would expect IT females to exhibit a different pattern of job mobility in relation to a relative pay gap than the pattern of job mobility described above.

Stigmatization. Stigmatization theory states that possessing a characteristic devalued in a particular social context (called a stigma) activates stereotypes in others (Crocker et al. 1998, Major and O'Brien 2005). Members of a social category are expected to behave in ways that are consistent with that social category's stereotype (Rudman and Phelan 2008). Disconfirming a social category's stereotype tends to attract "social and economic reprisals for behaving counterstereotypically" (Rudman and Phelan 2008, p. 61). Social reprisals are often in the form of verbal aggression, threats, and humiliation in the workplace (Harlos 2010), whereas economic reprisals tend to take the form of discounting the value of competencies and contributions (Tomaskovic-Devey and Skaggs 2002). The empirical studies of Blau and Tatum (2000) and von Hippel et al. (2011) show gender-based stereotyping and reprisals in organizations to be positively related to females leaving their jobs.

Being male, and thus assumed to be technically competent characterizes the stereotype of an IT professional (Enns et al. 2006). Being female in the IT profession disconfirms the IT stereotype, thereby attracting social and economic reprisals (Ahuja 2002, Trauth et al. 2009). Because stigmatization tends to permeate the IT profession (Leventman 2007, Trauth et al. 2009), we expect IT females to prefer to leave the IT profession.

We therefore hypothesize that for IT females, the larger the relative pay gap, the more likely it is that they will turn away-within or turn away-between than turn over. Leaving the IT profession may be less costly than expected because the stereotyping of IT females tends to discount returns to their IT-specific skills. By disconfirming the IT stereotype, IT females are thought to be less capable of undertaking technical work (Cohoon and Aspray 2006, Margolis and Fisher 2002). Therefore, IT females may be excluded from mainstream IT work (Adya 2008, p. 614). This exclusion from mainstream IT work is likely to lower the value of IT-specific human capital and make turnaway-within and -between less costly compared with turnover. However, turnaway-within is likely to remain less costly compared with turnaway-between because the latter discounts returns to both firm-specific and IT-specific human capital.

When taken together, the combination of distributive justice, human capital, and stigmatization theories suggests different patterns of job mobility associated with relative pay gaps for IT males and IT females. Hence, for IT males, we hypothesize the following:

Hypothesis 2A (H2A). *The larger the relative pay gap, the higher the likelihood that IT males will turn over than turn away-within.*

Hypothesis 2B (H2B). *The larger the relative pay gap, the higher the likelihood that IT males will turn over than turn away-between.*

Hypothesis 2C (H2C). *The larger the relative pay gap, the higher the likelihood that IT males will turn away-within than turn away-between.*

Conversely, for IT females we hypothesize the following:

Hypothesis 3A (H3A). *The larger the relative pay gap, the higher the likelihood that IT females will turn away-within than turn over.*

Hypothesis 3B (H3B). *The larger the relative pay gap, the higher the likelihood that IT females will turn away-between than turn over.*

Hypothesis 3C (H3C). *The larger the relative pay gap, the higher the likelihood that IT females will turn away-within than turn away-between.*

Method

This study's sample and data are drawn from a longitudinal archival data set containing demographics, labor market experiences, and pay information of individuals living in the United States. We test our hypotheses using a set of competing risks models of survival analyses (Allison 1984, Morita et al. 1993, Singer and Willett 1991) that evaluate the likelihood of IT professionals' turning over, turning away-within, or turning away-between. Competing risks models facilitate the analysis and comparison of multiple events that are independent of each other.

Data and Sample

The data span 28 years of work histories for a sample of IT professionals drawn from the National Longitudinal Survey of Youth (NLSY79). The Bureau of Labor Statistics (BLS) began the NLSY79 program in 1979 by surveying a nationally representative sample of 12,686 respondents between the ages of 14 and 21 (as of January 1, 1979). The NLSY79 remains an active survey program of the BLS. The BLS continues to interview this cohort to collect data on topics including work history, occupation, and income. The NLSY79 is ideal for this study because it contains work history data—detailed information on jobs and pay over individuals' careers (Bureau of Labor Statistics 2008).[2]

We used three criteria to draw this study's sample from the larger data set. First, we drew all respondents tracked from 1979 to 2006. Second, respondents must have attained at least a bachelor's degree. Third, respondents must have held an IT job as a permanent job at any point in their work history. The BLS defines a permanent job as one in which an incumbent has spent "one continuous year in a job" (Polivka 1996, p. 4). The preceding criteria exclude marginal workers in jobs that do not require a bachelor's degree and those who may have regarded IT jobs as temporary jobs. Temporary and marginal workers are argued to be unlikely to undergo the same processes as individuals within the primary labor market (Hulin et al. 1985).

IT jobs in the NLSY79 data set are identified by their U.S. Census Bureau Occupation Classification System (OCS) code (U.S. Census Bureau 1971, 2003). IT jobs in the OCS include computer and information systems managers, systems analysts, computer programmers, and technical specialists (e.g., computer support specialists, database administrators, and network administrators). Table 2 reports the number of respondents holding a particular IT job over the sampling period of our study and the proportion of females and males in each IT job.

Overall, our sample includes a total of 359 individuals: 162 (45.1%) females and 197 (54.9%) males. In terms of race, 78.6% of the sample is Caucasian, and the remaining 21.4% is non-Caucasian, including African Americans, Asians, and Pacific Islanders. Our selection criteria ensured that all respondents attained a bachelor's degree, including both non-IT majors (56.5%) and IT majors (43.5%), and 22% of the sample had postgraduate qualifications.

We further note that each individual in our sample contributed a number of detailed work history observations, which we refer to as *person-period observations*—one observation for each year that individual worked full-time in the workforce. For example, if a particular respondent was included in our sample, and worked full-time for each of the 10 years

[2] This research utilized the Bureau of Labor Statistics' restricted access GEOCODE data. The views expressed here do not necessarily reflect the views of the Bureau of Labor Statistics.

Table 2 IT Jobs and Proportions of IT Males and IT Females in IT Jobs

	N[a]	Percentage female (%)	Percentage male (%)
Computer and information systems managers	71	36.6	63.4
Systems analysts	101	33.7	66.3
Computer programmers	111	35.1	64.9
Technical specialists	214	52.8	47.2

[a]*N* refers to the number of individuals holding the particular IT job role over the sampling period. The total number of IT professionals in the IT job roles sums to greater than 359 because IT professionals may hold different IT job roles over the course of their work history.

during the sampling period of our study, that respondent would contribute 10 person-period observations (one for each year in the workforce). In sum, the total number of person-period observations for the 359 IT professionals in our sample was 6,219.

Measures

Table 3 lists the variables utilized in this study and their corresponding definitions. The following paragraphs provide details explaining how each variable was operationalized.

Dependent Variables. The dependent variables are the types of job mobility. Following prior studies that have also utilized the NLSY79 data set (e.g., Lee et al. 2008, Maltarich et al. 2010, Trevor and Nyberg 2008), we coded job mobility for each year of a respondent's work history based on the respondent's answers to multiple questions contained in the NLSY79. Specifically, we used information on the start and stop dates of employment, reason for leaving the job if the respondent changed jobs (i.e., quit to take another job), and the OCS codes for respondents' most recent and subsequent jobs.

Job Mobility was coded using respondents' start and stop dates of employment with an employer and reasons for leaving their job. *Job Mobility* was coded as 1 if a respondent started and voluntarily stopped employment on a particular job with an employer in a particular year. Otherwise, the respondent's *Job Mobility* was coded as 0 in that year.

We refined *Job Mobility* into *Turnover, Turnaway-Within*, and *Turnaway-Between* using respondents' start and stop dates of employment with an employer, reasons for leaving their job, and the OCS codes for respondents' most recent and subsequent jobs.

We coded *Turnover* as 1 if respondents started and stopped employment in a particular job with an employer, voluntarily left their job to take another job, and the OCS codes for their most recent and subsequent jobs were IT-related codes. Otherwise, *Turnover* was coded as 0.

We coded *Turnaway-Within* as 1 if respondents started but had not stopped employment with an employer, voluntarily left their job to take another job, and the OCS code for their most recent job was an IT-related code and the OCS code for their subsequent job was a non-IT code. Otherwise, *Turnaway-Within* was coded as 0.

We coded *Turnaway-Between* as 1 if respondents started and stopped employment on a particular job with an employer, voluntarily left their job to take another job, and the OCS code for their most recent job was an IT-related code and the OCS code for their subsequent job was a non-IT code. Otherwise, *Turnaway-Between* was coded as 0.

Independent Variables. The independent variable is relative pay gap. *Relative Pay Gap* is operationalized as a ratio of the average male's pay to an individual's pay, given a particular job and level of job tenure. *Relative Pay Gap* is a lagged time-varying predictor of job mobility in the analyses. *Relative Pay Gap* is lagged by one year because the strength and relevance of a predictor's relationship with a dependent variable decreases with time (Griffeth et al. 2000, Kelly and McGrath 1988). Lagging a variable also mitigates the possibility of simultaneity bias between the independent and dependent variables (Singer and Willett 1991, p. 441).

This study follows a three-step process utilized in prior research to compute the relative pay gap (e.g., Blau and Kahn 1981, Gupta et al. 2006, Trevor and Nyberg 2008, Viscusi 1980) for each respondent in each year of their work history. First, we computed respondents' *Real Hourly Pay* for each job in each year from reported nominal hourly pay using a consumer price index (CPI) deflator, with 1982–1984 as the base year (Bureau of Labor Statistics 2009). Second, we computed the mean real hourly pay of males for each job category and level of job tenure occurring in our data set (e.g., IT manager with five years of job tenure or systems analyst with three years of job tenure). Third, we computed *Relative Pay Gap* as a ratio measure of the mean real hourly pay of males to each respondent's real hourly pay, given a job category and for a level of job tenure. A relative pay gap greater than one suggests that, all else being equal, a respondent is earning less than the "going" rate for males in that particular job and level of job tenure.

We use average male hourly pay for a given job category and job tenure as the referent for three reasons. One, the average male pay is argued to be the benchmark for the long-run expected pay in a job (Blau and Kahn 1981). Two, the relative pay gap is a proxy to estimate the difference in pay associated with biases experienced by one group compared to another (Gupta et al. 2006). Three, the relative pay gap measures the potential attractiveness or utility of a job

Table 3 Variables and Corresponding Definitions

Variable	Definition
Dependent variables	
Job Mobility	Voluntarily leaving an IT job
Turnover	Voluntarily leaving an IT job for an alternative IT job with a different firm
Turnaway-Within	Voluntarily leaving an IT job for an alternative non-IT job within one's firm
Turnaway-Between	Voluntarily leaving an IT job for an alternative non-IT job in a different firm
Independent variables	
Relative Pay Gap	Ratio of the average male's pay to the respondent's pay, given a particular job and job tenure
Moderator variable	
Sex	Biological classification of female or male
Controls—Human capital	
Cognitive Ability	Measure of general ability
Education Level	Level of schooling
Manufacturing; Professional, Business, or Finance; and *Retail and Trade*	The Standard Industrial Classification code of respondent's job, with *All Other Industries* as the reference
IT Education	Enrolled in an IT-related major while in college
Systems Analyst, Computer Programmer, and *Technical Specialist*	Job type while in the IT profession, with *IT Manager* as the reference
IT-Specific Experience and *IT-Specific Experience* (*squared*)	Tenure in IT profession
Firm-Specific Training	Firm sponsored training received with a particular firm
Firm-Specific Experience and *Firm-Specific Experience* (*squared*)	Tenure in a particular firm
Controls—Desire to move	
Job Status	Socioeconomic status of a job
Job Satisfaction	Affective attachment to a job
Controls—Ease of movement	
Enrolled in School and *Unemployed*	Respondent's labor force participation status, with *Employed* as the reference.
Unemployment Rate	Local rate of joblessness in respondent's geographic location in the U.S.
Controls—Demographics	
Race	The reported ethnic affiliation of respondent, with *Nonwhite* as the reference
Marital Status	Whether respondent is married; with *Not Married* as the reference
Number of Children	Number of children in respondent's household
South, Northeast, and Midwest	Respondent's geographic region of residence within the United States with *West and Pacific* as the reference
Urban	Respondent's residence is within a city area, with *Nonurban* as the reference
Real Hourly Pay	Hourly pay adjusted using the consumer price index deflator (1982–1984)

vis-à-vis alternative jobs (England et al. 2007, Reskin et al. 1999).

Control Variables. Twenty-seven control variables account for alternative explanations of job mobility, such as human capital (Ang et al. 2002, Becker 1975) and organizational equilibrium (Joseph et al. 2007, March and Simon 1958) theories.

Human capital factors included in this study are general, industry, IT-specific, and firm-specific human capital. General human capital measures include respondents' cognitive ability and education level. *Cognitive Ability* is a time-invariant percentile score from the Armed Forces Qualifying Test (AFQT) administered to the NLSY79 sample in 1980. The AFQT percentile score is a composite of four quantitative and verbal tests: mathematical knowledge, arithmetic reasoning, paragraph comprehension, and work knowledge.

Education Level is a time-varying dichotomous variable coded as 1 if and when a respondent attains a postgraduate degree; otherwise it is coded as 0 to denote attainment of a bachelor's degree.

We use three time-varying dummy variables to represent industry-specific human capital. The following industries are the most frequently occurring reported by respondents. We used the U.S. Census' Standard Industrial Classification (U.S. Census Bureau 1971, 2003) to code *Manufacturing* as 1 if a respondent reported a job in a manufacturing industry, *Professional, Business, or Finance* industries as 1 if a respondent reported a job in that industry, and *Retail and Trade* as 1 if a respondent reported a job in that industry. Otherwise, the dummy codes were 0.

IT-specific human capital measures are IT-specific education, IT job type, and IT experience. *IT Education* is a time-invariant dichotomous variable coded as 1 if the IT discipline was the respondent's major field of study in college, and coded as 0 otherwise.

We noted each respondent's IT job using IT-specific OCS codes created by NLSY79. IT job type is represented by lagged time-varying dummy variables to represent *Systems Analyst* (coded as 1), *Computer Programmer* (coded as 1), and *Technical Specialist* (coded as 1), with *IT Managers* as the reference group (coded as 0).

IT-Specific Experience is a lagged time-varying measure in years, based on the start and end dates of IT jobs held by each respondent.

The firm-specific human capital variables include *Firm-Specific Training* and *Firm-Specific Experience*. *Firm-Specific Training* represents the accumulated number of firm-specific training events a respondent received in a particular firm. This lagged time-varying covariate is constructed from respondents' answers to whether they had received training with an employer during the course of a year and the kind of training received (i.e., on-the-job training).

Firm-Specific Experience is a lagged time-varying measure in years based on the start and end dates of a respondent's job with a particular firm. We follow prior human capital literature (e.g., Mincer 1974) by including squared terms of IT-specific and firm-specific experience to model nonlinear relationships between the experience variables and the dependent variables.

Following organizational equilibrium theory (March and Simon 1958) and related empirical studies, we control for desire and ease of movement. We operationalized desire to move with job status and job satisfaction. The *Job Status* variable is measured using the Duncan Socioeconomic Index (SEI; Duncan 1961). The Duncan SEI provides a prestige score for each occupation ranging from 0 (lowest) to 97 (highest). This time-varying measure represents the attractiveness of a respondent's current job vis-à-vis other jobs (Mayer and Schoorman 1998).

We follow prior studies (e.g., Dickter et al. 1996, Ganzach 1998, Gerhart 1987, Trevor 2001) in using a lagged time-varying measure of *Job Satisfaction* from the NLSY79. The job satisfaction measure in the NLSY79 is a single item providing a general indication of respondents' affective attachment to their jobs. This single item measure has shown substantial convergent validity (Wanous et al. 1997) with patterns of results similar to multiple item measures of job satisfaction (Ganzach 1998).

We operationalized ease of movement with labor force status and unemployment rate. Labor force status is represented by two time-varying dummy variables. The first, *Enrolled in School*, was coded as 1 if a respondent reported being concurrently enrolled in school; otherwise it was coded as 0. The second, *Unemployed*, was coded as 1 using NLSY79's coding of respondents' labor force status following the Bureau of Labor Statistics' (2008, Table 4.27.1, p. 219) definition of unemployment as "temporarily not in a job and actively seeking employment"; otherwise it was coded as 0.

Unemployment Rate is a time-varying measure of the local unemployment rates in respondents' geographic locations. This measure is computed and provided by NLSY79 in its restricted access GEOCODE data set.

We control for demographic factors known to influence job mobility (Joseph et al. 2012). We coded *Race* as 1 if racial affiliation was reported as "white." Otherwise, race was coded as 0. *Marital Status*, a time-varying measure, was coded as 1 if the respondent reported being married at a given time; otherwise, it was coded as 0. The *Number of Children* in a respondent's household was reported in each time period and is also a time-varying, continuous measure.

Information for respondents' state and urban area of residence was obtained from NLSY79's restricted access GEOCODE data. We follow prior research (e.g., Blau and Kahn 1981) and NLSY79's coding scheme to include three time-varying dummies indicating individuals' region of residence as the *South* (coded as 1), *Northeast* (coded as 1), and *Midwest* (coded as 1) in the United States, with *West and Pacific* as the reference (coded as 0).

Urban area of residence is denoted by a dummy variable, *Urban* (coded as 1), with *Nonurban* (coded as 0) as the reference. NLSY79's coding of urban and rural residences for respondents is based on census population data in the NLSY79 restricted access GEOCODE.

Data Analysis

We employed survival analysis to estimate the effect of a relative pay gap on job mobility. Survival analysis is a statistical approach that accounts for the timing of individuals' job moves and provides insight into why such moves occur (Dickter et al. 1996). Models in survival analysis account for the effects of time by including a measure of "time to an event" (Hosmer and Lemeshow 1999, p. 2), in our case the time to each job move. For example, turnover research (Hom et al. 2008) indicates that firm tenure has a curvilinear relationship with turnover, suggesting that turnover is less likely with increasing firm-specific experience. As such, considering *when* job mobility occurs is as important and relevant as understanding *why* such moves occur (Peters and Sheridan 1988).

We use a Cox regression for the survival analysis (Cox 1972) for three reasons. First, Cox regression allows predictors to be included in a standard regression form, allowing easy interpretation of the results (Allison 1995). Second, Cox regression accounts for the influence of truncation and censoring of observations (Hosmer and Lemeshow 1999). The data assembled for this study are left truncated and right censored because of the sample selection criteria and study design. Finally, Cox regression does not require the specification of the baseline hazard, which is required in other forms of survival analyses (Allison 1995). The baseline hazard is the hazard of an event in the absence of covariates (Hosmer and Lemeshow 1999). The form of the baseline hazard is typically not normally distributed, known, or theorized in turnover research (Morita et al. 1989, 1993).

Competing Risks Model. This study tests the hypotheses using competing risks models of survival analyses (Allison 1984, Morita et al. 1993, Singer and Willett 1991). The assumption underlying competing risks models is that events are independent of each other (Allison 1984, Singer and Willett 2003). In other words, the occurrence of one type of event removes individuals from the risk of all other types of events at that particular time. In this study, IT professionals can only perform one type of job mobility at any given time. Undertaking a particular type of job mobility removes IT professionals from the risk of enacting all other types of job mobility at that time.

The null hypothesis is that the coefficients for relative pay gap are not significantly different from each other across the types of job mobility. Each type of job mobility is estimated separately, and the equality of coefficients across these models is tested using a one-degree-of-freedom Wald chi-square statistic (Allison 1995, Hosmer and Lemeshow 1999). A significant Wald chi-square statistic rejects the null hypothesis and indicates that the likelihood of one job mobility is higher or lower than another in relation to a relative pay gap.

Censoring Other Forms of Movement. Following the approach used in the literature (e.g., Lee et al. 2008, Trevor 2001), other types of job mobility (e.g., involuntary quits, leaving for higher education, or leaving the workforce) were censored because they are outside the scope of this study. Unlike traditional research designs, censoring is not problematic for survival analysis because it utilizes information from all observations up to the point of censoring to estimate hazard rates (Dickter et al. 1996, Morita et al. 1989).

Repeated Events and Observations. Job mobility is a repeated event in respondents' work histories. Each respondent also provides multiple observations. Repeated events and multiple observations per respondent violate the assumption of independence of observations by biasing standard errors and coefficients (Allison 1984, Hosmer and Lemeshow 1999).

We correct for nonindependence of observations using a robust variance estimator advocated by Lin and Wei (1989). The robust variance estimator does not require assumptions of a specific structure for the dependence among events or observations (Morita et al. 1993). Instead, the robust variance estimator computes standard errors from pooled within-respondent error residuals (Hosmer and Lemeshow 1999).

Stratified Analysis. The distributions of job mobility are known to be significantly different for IT males and IT females (Joseph et al. 2007, 2012). The gender difference in the distribution of job mobility is attributed to the dissimilar work experiences of IT females and IT males (e.g., Ahuja 2002, Leventman 2007). The different distributions of job mobility threaten to violate the assumption of proportional hazards. The assumption of proportional hazards requires the hazard function for all respondents to be a constant multiple or proportion of the baseline hazard (Allison 1984, Hosmer and Lemeshow 1999).

We tested the equality of job mobility distributions for IT males and IT females with log rank tests. The log rank tests indicate that IT males and IT females have significantly different distributions of job mobility ($\chi^2 = 5.82$, df $= 1$, $p < 0.05$), turnover ($\chi^2 = 22.00$, df $= 1$, $p < 0.001$), and turnaway-within ($\chi^2 = 4.17$, df $= 1$, $p < 0.05$), and marginally different distributions for turnaway-between ($\chi^2 = 3.55$, df $= 1$, $p = 0.059$). These results indicate a violation of the assumption of proportional hazards.

As recommended by Allison (1984) and Hosmer and Lemeshow (1999), we resolved this violation with a stratified Cox regression. A stratified analysis is performed by first fitting hypothesized models to all data, ignoring the gender of the respondent. Second, hypothesized models are analyzed separately by gender. Third, a stratification test is conducted to ascertain whether the stratified model fits the data better than a combined model (Singer and Willett 2003, pp. 560–561). A significant difference between the log-likelihoods of the stratified and combined models indicates model fit (Allison 1995, Singer and Willett 2003).

The model stratification tests confirm a stratified model for job mobility ($\chi^2 = 949.11$, df $= 28$, $p < 0.001$), turnover ($\chi^2 = 641.56$, df $= 28$, $p < 0.001$), turnaway-within ($\chi^2 = 210.32$, df $= 28$, $p < 0.001$), and turnaway-between ($\chi^2 = 150.25$, df $= 28$, $p < 0.001$). The tests indicate that IT males and IT females have different likelihoods of job mobility for the examined set of predictors and that their data should be analyzed separately.

Results

The means, standard deviations, and correlations are presented in Table 4. Table 5 presents the results for the competing risks models of job mobility: turnover, turnaway-within, and turnaway-between. The coefficients (β) in Table 5 are interpreted as odds ratios, a comparative measure of event occurrence (Hosmer and Lemeshow 1999).

Table 4 Means, Standard Deviations, and Correlations of Study Variables for IT Males and IT Females

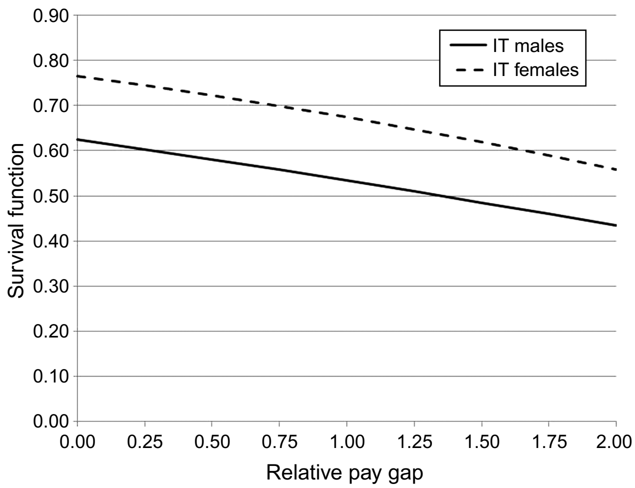
	IT males		IT females															
	Mean	SD	Mean	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1 *Turnover*	0.091	0.288	0.057	0.232		−0.041	−0.033	0.016	−0.017	0.030	0.017	−0.011	−0.047	0.042	0.008	0.049	−0.028	0.016
2 *Turnaway-Within*	0.016	0.126	0.023	0.149	−0.038		−0.013	−0.029	0.011	0.020	−0.013	−0.026	0.003	−0.010	0.000	−0.016	−0.023	−0.008
3 *Turnaway-Between*	0.010	0.102	0.015	0.122	−0.031	−0.019		0.005	−0.021	−0.007	0.006	−0.026	0.031	−0.001	−0.007	0.013	0.019	−0.008
4 Region: *South*	0.350	0.477	0.419	0.493	0.048	−0.006	0.041		−0.473	−0.365	−0.139	−0.137	−0.005	0.004	−0.049	−0.100	0.040	−0.235
5 Region: *Northeast*	0.293	0.455	0.307	0.461	−0.030	0.021	−0.020	−0.565		−0.320	0.097	0.100	0.039	0.049	−0.078	0.127	−0.007	0.132
6 Region: *Midwest*	0.198	0.399	0.091	0.287	0.006	−0.040	0.001	−0.268	−0.210		0.012	−0.061	−0.033	−0.047	−0.058	0.079	−0.029	0.117
7 *Urban*	0.660	0.474	0.699	0.459	−0.026	0.018	−0.007	−0.051	0.098	−0.098		−0.162	−0.013	0.020	0.007	0.032	−0.008	−0.013
8 *Unemployment Rate*	6.161	2.700	6.198	2.790	−0.056	−0.024	−0.025	−0.116	0.015	0.007	−0.235		0.085	0.141	0.016	0.004	0.039	0.034
9 *Enrolled in School*	0.033	0.178	0.029	0.169	−0.007	0.015	−0.005	0.016	−0.031	0.032	−0.030	0.047		0.327	−0.042	−0.009	0.087	0.016
10 *Unemployed*	0.118	0.323	0.162	0.368	0.023	−0.010	0.078	0.059	−0.051	−0.040	−0.037	0.099	0.143		−0.017	−0.004	0.112	−0.025
11 Industry—*Manufacturing*	0.167	0.373	0.083	0.276	0.019	0.014	−0.006	−0.077	0.123	−0.060	0.006	−0.008	−0.007	0.030		−0.406	−0.160	0.011
12 Industry—*Professional, Business, or Finance*	0.451	0.498	0.493	0.500	0.059	−0.010	0.033	0.020	−0.021	−0.002	0.012	−0.020	0.015	0.019	−0.296		−0.324	0.054
13 Industry—*Retail and Trade*	0.113	0.317	0.113	0.316	−0.030	0.027	0.020	−0.026	0.008	−0.016	0.021	0.046	0.004	0.039	−0.107	−0.351		−0.016
14 *Race*	0.807	0.396	0.759	0.429	0.019	0.006	−0.022	−0.246	0.185	0.057	−0.146	0.011	−0.039	−0.056	0.134	−0.115	0.045	
15 *Marital Status*	0.552	0.497	0.488	0.500	0.019	0.006	0.023	0.027	0.020	−0.033	−0.151	−0.138	−0.062	−0.041	0.017	−0.052	−0.062	0.227
16 *Number of Children*	0.644	1.032	0.756	1.031	−0.003	−0.016	0.010	0.045	−0.092	0.035	−0.134	−0.095	0.003	0.042	−0.046	−0.024	−0.080	−0.106
17 *Job Status*	60.427	17.807	55.808	20.193	0.072	0.039	0.011	−0.015	0.023	0.015	0.017	−0.173	−0.058	−0.070	0.123	0.127	−0.153	0.090
18 *Job Satisfaction* (lag)	2.793	1.368	2.586	1.485	0.037	−0.082	−0.002	0.035	0.009	0.020	0.043	−0.059	−0.063	−0.185	0.040	−0.001	−0.055	0.053
19 *Cognitive Ability*	76.756	22.086	67.224	25.455	0.061	0.001	−0.033	−0.231	0.256	0.038	0.005	−0.040	−0.034	−0.033	0.129	−0.025	−0.059	0.515
20 *Education Level*	0.218	0.413	0.233	0.423	−0.003	−0.017	0.014	0.002	−0.007	−0.024	0.102	−0.036	0.017	0.015	−0.018	0.066	−0.078	0.044
21 *IT Education*	0.508	0.501	0.346	0.477	0.093	−0.021	−0.023	0.112	−0.036	0.029	−0.104	0.071	−0.012	−0.034	0.049	0.001	0.005	−0.107
22 Job type: *Systems Analyst* (lag)	0.150	0.357	0.092	0.289	0.094	−0.016	0.011	0.013	0.065	0.031	0.008	−0.086	−0.012	0.018	0.054	0.026	−0.040	0.129
23 Job type: *Computer Programmer* (lag)	0.146	0.353	0.067	0.249	0.116	0.053	0.048	−0.016	0.060	0.009	−0.008	−0.030	−0.038	−0.041	0.017	0.004	−0.020	0.046
24 Job type: *Technical Specialist* (lag)	0.239	0.427	0.232	0.422	0.155	0.161	0.123	0.060	−0.099	0.081	−0.077	0.012	−0.012	−0.005	0.013	0.052	0.004	−0.019
25 *IT-Specific Experience* (lag)	5.791	5.987	4.220	5.207	0.174	0.085	0.048	0.092	−0.017	0.060	−0.064	−0.215	−0.026	−0.102	0.143	−0.012	−0.073	0.149
26 *IT-Specific Experience* (squared, lag)	69.371	113.928	44.913	93.700	0.131	0.092	0.034	0.088	−0.028	0.052	−0.050	−0.173	0.001	−0.067	0.113	−0.017	−0.053	0.124
27 *Firm-Specific Training* (lag)	0.549	1.012	0.453	0.885	0.023	0.010	−0.005	−0.026	0.031	0.098	0.000	−0.104	−0.033	−0.098	0.013	−0.085	−0.084	0.082
28 *Firm-Specific Experience* (lag)	4.074	4.339	3.908	4.426	0.002	−0.005	0.005	−0.022	0.033	0.000	0.045	−0.157	−0.067	−0.157	0.070	−0.106	−0.038	0.026
29 *Firm-Specific Experience* (squared, lag)	35.419	70.645	34.849	72.337	−0.016	0.010	−0.005	−0.030	0.031	−0.011	0.041	−0.137	−0.046	−0.112	0.073	−0.100	−0.028	0.017
30 *Real Hourly Pay* (lag)	12.204	7.060	9.016	5.248	0.124	0.025	−0.015	−0.112	0.096	−0.017	0.096	−0.206	−0.076	−0.152	0.181	−0.050	−0.132	0.174
31 *Relative Pay Gap* (lag)	1.250	0.709	1.542	0.882	−0.029	0.029	0.074	0.103	−0.141	0.033	−0.105	0.129	0.046	0.105	−0.082	0.017	0.088	−0.119

Table 4 (Continued)

	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31
1 *Turnover*	0.016	0.005	0.080	0.043	0.033	−0.003	0.076	0.053	0.104	0.143	0.106	0.066	−0.020	−0.034	−0.048	0.059	−0.015
2 *Turnaway-Within*	0.011	0.030	0.022	−0.064	−0.003	−0.010	−0.040	−0.001	0.008	0.067	0.089	0.106	0.024	0.014	0.016	0.033	0.014
3 *Turnaway-Between*	−0.014	0.027	−0.029	0.028	−0.025	0.031	−0.022	0.006	0.007	0.087	0.008	−0.011	0.002	−0.014	−0.021	−0.017	0.035
4 Region: *South*	0.076	0.003	−0.047	0.010	−0.230	−0.041	0.017	0.013	−0.117	0.097	0.020	0.019	0.090	0.018	0.019	−0.036	−0.002
5 Region: *Northeast*	−0.092	−0.076	−0.005	−0.045	0.092	0.061	−0.001	0.005	0.012	−0.064	−0.060	−0.051	−0.064	−0.041	−0.033	0.015	0.046
6 Region: *Midwest*	0.054	0.055	0.090	0.011	0.134	−0.043	−0.036	−0.049	0.153	−0.028	0.085	0.072	−0.013	0.041	0.038	0.013	−0.023
7 *Urban*	−0.123	−0.151	0.088	−0.013	0.052	0.019	−0.045	0.012	0.082	−0.081	−0.157	−0.172	−0.022	−0.122	−0.137	0.055	−0.057
8 *Unemployment Rate*	−0.118	−0.080	−0.166	−0.081	0.060	0.041	0.012	−0.065	0.028	−0.024	−0.166	−0.137	−0.147	−0.162	−0.142	−0.194	0.087
9 *Enrolled in School*	−0.147	−0.092	−0.185	−0.163	0.029	0.069	−0.056	−0.054	−0.010	−0.084	−0.137	−0.085	−0.080	−0.128	−0.084	−0.121	0.041
10 *Unemployed*	−0.253	−0.179	−0.219	−0.262	−0.033	0.009	−0.035	−0.052	−0.049	−0.084	−0.252	−0.174	−0.154	−0.230	−0.157	−0.234	0.083
11 Industry—*Manufacturing*	0.056	0.025	0.042	0.027	−0.008	−0.009	0.068	0.054	0.007	0.086	0.031	0.004	0.018	0.061	0.053	0.070	−0.115
12 Industry—*Professional, Business, or Finance*	−0.002	0.026	0.138	0.011	0.137	0.102	−0.025	0.035	0.055	−0.011	0.018	0.002	−0.066	−0.070	−0.076	0.063	0.026
13 Industry—*Retail and Trade*	−0.119	−0.063	−0.214	−0.093	−0.044	−0.054	0.029	−0.053	−0.057	−0.108	−0.092	−0.032	−0.077	−0.069	−0.028	−0.160	0.135
14 *Race*	0.053	−0.019	0.098	0.036	0.495	0.131	0.033	−0.008	0.027	−0.010	0.028	0.028	−0.009	0.007	−0.006	0.108	−0.058
15 *Marital Status*		0.528	0.182	0.163	0.037	−0.002	−0.012	0.103	−0.092	0.084	0.336	0.264	0.198	0.262	0.203	0.351	−0.206
16 *Number of Children*	0.476		0.125	0.128	0.006	0.071	−0.049	−0.037	−0.062	0.080	0.354	0.306	0.207	0.225	0.172	0.317	−0.141
17 *Job Status*	0.062	−0.071		0.188	0.147	0.090	−0.007	0.174	0.099	−0.038	0.294	0.224	0.140	0.189	0.149	0.426	−0.151
18 *Job Satisfaction* (lag)	0.033	−0.025	0.181		0.017	0.021	0.003	0.095	0.031	0.055	0.166	0.091	0.134	0.298	0.158	0.188	−0.037
19 *Cognitive Ability*	0.129	−0.084	0.259	0.021		0.219	0.015	0.095	0.140	−0.099	0.118	0.113	0.027	0.079	0.070	0.202	−0.136
20 *Education Level*	0.013	−0.131	0.198	0.036	0.188		−0.182	0.008	−0.056	0.001	−0.030	−0.037	−0.032	−0.049	−0.050	0.095	0.001
21 *IT Education*	0.029	0.035	0.114	0.026	−0.059	−0.037		0.110	0.158	−0.043	0.152	0.144	0.023	−0.005	−0.014	−0.008	−0.028
22 Job type: *Systems Analyst* (lag)	0.109	0.093	0.189	0.086	0.171	0.023	0.108		−0.174	−0.236	0.188	0.105	0.011	0.133	0.116	0.137	0.008
23 Job type: *Computer Programmer* (lag)	−0.002	−0.043	0.097	0.030	0.068	0.026	0.125	−0.085		−0.232	0.016	−0.037	0.035	−0.081	−0.083	−0.033	−0.067
24 Job type: *Technical Specialist* (lag)	0.025	0.017	−0.074	0.056	−0.064	−0.108	0.091	−0.175	−0.147		0.206	0.138	0.053	0.049	0.027	0.017	−0.024
25 *IT-Specific Experience* (lag)	0.214	0.274	0.217	0.134	0.143	−0.031	0.241	0.303	0.047	0.242		0.937	0.288	0.525	0.492	0.471	−0.189
26 *IT-Specific Experience* (squared, lag)	0.167	0.240	0.165	0.079	0.133	−0.033	0.211	0.244	−0.014	0.162	0.929		0.250	0.494	0.508	0.412	−0.156
27 *Firm-Specific Training* (lag)	0.108	0.152	0.182	0.165	0.109	0.018	0.053	0.186	0.021	0.069	0.306	0.242		0.450	0.387	0.213	−0.093
28 *Firm-Specific Experience* (lag)	0.094	0.154	0.164	0.331	0.051	0.008	0.041	0.134	−0.047	0.051	0.361	0.302	0.436		0.934	0.287	−0.043
29 *Firm-Specific Experience* (squared, lag)	0.051	0.129	0.109	0.180	0.041	0.009	0.035	0.096	−0.050	0.037	0.316	0.284	0.369	0.932		0.219	−0.039
30 *Real Hourly Pay* (lag)	0.168	0.107	0.432	0.240	0.350	0.091	0.115	0.271	0.046	0.006	0.464	0.409	0.350	0.359	0.285		−0.571
31 *Relative Pay Gap* (lag)	−0.045	0.000	−0.180	−0.033	−0.234	−0.043	−0.005	−0.097	−0.046	0.110	−0.097	−0.079	−0.138	−0.049	−0.044	−0.535	

Notes. There are a total of 6,578 person-period observations. After lagging time-varying independent variables, 359 first period observations were dropped. The remaining total of 6,219 person-period observations were used for subsequent analyses. For IT males, descriptives and correlations between time-varying variables or between time-varying and time-invariant variables were obtained from cross-sectional time series data covering 3,356 person-period observations. Descriptives and correlations between time-invariant variables were obtained from 197 IT males. For IT females, descriptives and correlations between time-varying variables or between time-varying and time-invariant variables were obtained from cross-sectional time series data covering 2,863 person-period observations. Descriptives and correlations between time-invariant variables were obtained from 162 IT females. Correlations for IT females are reported below the diagonal.

Figure 2 Survivor Functions for IT Males and IT Females



Distributive Justice

Hypothesis 1 states that the larger the relative pay, the higher the likelihood of a job move. Results from the Cox regression on job mobility support Hypothesis 1 (Table 5) for both IT males and IT females. Specifically, we find that the larger the relative pay, the higher the likelihood of a job move for IT males (Model 1, $\beta = 0.286$, $p < 0.001$) and IT females (Model 5, $\beta = 0.392$, $p < 0.001$).

Because staying (Table 1, Cell 1) is the reference category in this hypothesis, the results may also be interpreted symmetrically as the larger the relative pay gap, the lower the likelihood of staying. Graphing the results for IT males (Model 1) and IT females (Model 5), we find that the probability of staying decreases as relative pay gap increases for both IT males and IT females (Figure 2). From Figure 2, we see that at a relative pay gap of 0.50 (i.e., the individual's pay is greater than the average male's in the same job with the same tenure, all else equal), the likelihood of staying with the current job is 58% for IT males and 72% for IT females. However, when the relative pay gap is greater, such as at 1.50 (i.e., the individual's pay is less than that of the average male in the same job with the same tenure, all else equal), the likelihood of staying with the current job is 48% for IT males and 62% for IT females.

Human Capital and Stigmatization

IT Males. Hypothesis 2A states that the larger the relative pay gap, the higher the likelihood that IT males will turn over than turn away-within. The test of equality of relative pay gap coefficients does not support Hypothesis 2A (Wald $\chi^2 = 18.490$, df $= 1$, $p < 0.001$). We find that the larger the relative pay gap, the more likely it is that IT males will turn away-within (Model 3, $\beta = 0.508$, $p < 0.001$) than turn over (Model 2, $\beta = 0.244$, $p < 0.01$).

Hypothesis 2B states that the larger the relative pay gap, the higher the likelihood that IT males will turn over than turn away-between. The test of equality of relative pay gap coefficients supports Hypothesis 2B (Wald $\chi^2 = 4.170$, df $= 1$, $p < 0.05$). We find that the larger the relative pay gap, the more likely it is that IT males will turn over (Model 2, $\beta = 0.244$, $p < 0.01$) than turn away-between (Model 4, $\beta = 0.161$, nonsignificant (ns)).

Hypothesis 2C states that the larger the relative pay gap, the higher the likelihood that IT males will turn away-within a firm than turn away-between. The test of equality of relative pay gap coefficients supports Hypothesis 2C (Wald $\chi^2 = 27.174$, df $= 1$, $p < 0.001$). We find that the larger the relative pay gap, the more likely it is that IT males will turn away-within (Model 3, $\beta = 0.508$, $p < 0.001$) than turn away-between (Model 4, $\beta = 0.161$, ns).

In sum, the results support two of our three hypotheses for IT males. The results show that the larger the relative pay gap, the higher the likelihood that IT males will turn away-within than turn over, and more likely to turn over than turn away-between.

IT Females. Hypothesis 3A states that the larger the relative pay, the higher the likelihood that IT females will turn away-within than turn over. The test of equality of relative pay gap coefficients confirms support for Hypothesis 3A (Wald $\chi^2 = 10.933$, df $= 1$, $p < 0.001$). We find that the larger the relative pay gap, the higher the likelihood that IT females will turn away-within (Model 7, $\beta = 0.501$, $p < 0.01$) than turn over (Model 6, $\beta = 0.311$, $p < 0.05$).

Hypothesis 3B states that the larger the relative pay, the higher the likelihood that IT females will turn away-between than turn over. The test of equality of relative pay gap coefficients confirms support for Hypothesis 3B (Wald $\chi^2 = 25.323$, df $= 1$, $p < 0.001$). We find that the larger the relative pay gap, the higher the likelihood that IT females will turn away-between (Model 8, $\beta = 0.574$, $p < 0.001$) than turn over (Model 6, $\beta = 0.311$, $p < 0.05$).

Hypothesis 3C states that the larger the relative pay gap, the higher the likelihood that IT females will turn away-within than turn away-between. The test of equality of relative pay gap coefficients does not support Hypothesis 3C (Wald $\chi^2 = 1.478$, df $= 1$, ns). We find that IT females are as likely to turn away-within (Model 7, $\beta = 0.501$, $p < 0.01$) as they are to turn away-between (Model 8, $\beta = 0.574$, $p < 0.001$).

In sum, the results show that the larger the relative pay gap, the higher the likelihood that IT females will turn away (within or between firms) than turn over.

Table 5 IT Females' and IT Males' Job Mobility Responses to a Relative Pay Gap

	IT males				IT females			
	Model 1	Model 2	Model 3	Model 4	Model 5	Model 6	Model 7	Model 8
	Job mobility	Turnover	Turnaway-within	Turnaway-between	Job mobility	Turnover	Turnaway-within	Turnaway-between
	β	β	β	β	β	β	β	β
Region: *South*	0.001	0.280	−0.887*	−0.677	0.199	0.416	−0.262	0.991
Region: *Northeast*	−0.018	0.112	0.190	−0.785	−0.038	−0.125	0.176	0.639
Region: *Midwest*	0.096	0.213	0.144	−0.364	−0.250	0.108	−1.912	0.776
Urban	0.073	0.096	−0.155	−0.043	0.156	0.092	0.342	0.253
Unemployment Rate	−0.005	0.008	−0.072	−0.118	−0.025	−0.045	−0.004	0.049
Enrolled in School	−0.304	−1.349	0.015	2.290***	0.204	−0.299	0.777	−0.109
Unemployed	0.748***	0.904***	0.254	0.077	0.517***	0.571**	−0.355	1.251***
Industry—*Manufacturing*	0.016	0.150	−0.275	0.160	0.130	0.148	0.175	0.508
Industry—*Professional, Business, or Finance*	0.077	0.197	−0.740*	0.803	0.232	0.331	−0.262	0.829
Industry—*Retail and Trade*	0.313	0.384	−0.688	1.763*	0.345	−0.053	0.477	1.208*
Race	−0.081	−0.052	−0.439	0.282	−0.092	−0.336	0.135	0.165
Marital Status	0.045	0.164	−0.210	−0.850	−0.018	−0.004	−0.141	0.130
Number of Children	0.009	−0.039	0.088	0.334	−0.131	−0.158	−0.134	0.048
Job Status	0.011*	0.019**	0.003	−0.033	0.023***	0.008	0.050***	0.030
Job Satisfaction (lag)	0.000	0.063	−0.372***	0.237	−0.102*	0.039	−0.410***	−0.130
Cognitive Ability	0.001	0.003	0.002	−0.016	−0.002	0.007	−0.011	−0.015
Education Level	0.002	−0.001	−0.302	1.029**	0.033	−0.108	0.190	0.583
IT Education	0.026	0.253*	−1.127***	−0.278	−0.281*	0.076	−0.854**	−0.968*
Job type: *Systems Analyst* (lag)	1.696***	1.672***	1.360*	3.060*	1.968***	1.694***	1.790*	2.683**
Job type: *Computer Programmer* (lag)	2.113***	2.170***	1.568**	3.359**	2.828***	2.306***	3.124***	3.985***
Job type: *Technical Specialist* (lag)	2.284***	2.306***	1.745***	3.452***	2.824***	2.145***	3.564***	3.789***
IT-Specific Experience (lag)	0.032	0.069	−0.078	0.170	0.068	0.178**	−0.049	−0.071
IT-Specific Experience (squared, lag)	0.000	−0.002	0.007*	−0.013	−0.002	−0.007**	0.005	0.001
Firm-Specific Training (lag)	−0.051	−0.116	0.150	0.139	−0.093	−0.151	0.103	−0.094
Firm-Specific Experience (lag)	0.037	0.050	0.032	0.128	0.023	0.041	−0.095	0.236
Firm-Specific Experience (squared, lag)	−0.007*	−0.008	−0.006	−0.017	−0.004	−0.006	0.003	−0.016
Real Hourly Pay (lag)	0.030*	0.031*	0.022	−0.019	0.067***	0.085***	0.043	0.057
Relative Pay Gap (lag)	0.286***	0.244**	0.508***	0.161	0.392***	0.311*	0.501**	0.574***
Generalized R^2 (%)	81.62	86.25	50.44	50.60	90.66	95.01	76.43	55.83
Change in generalized R^2 due to *Relative Pay Gap* (%)	3.98	4.62	5.13	1.06	2.40	0.32	1.57	1.11
Log likelihood ratio χ^2	333.73***	390.86***	138.30***	138.91***	384.12***	485.65***	234.15***	132.36***
df	28	28	28	28	28	28	28	28
N	197	197	197	197	162	162	162	162
Observations	3,356	3,350	3,355	3,356	2,863	2,858	2,862	2,862

$^{*}p < 0.05$; $^{**}p < 0.01$; $^{***}p < 0.001$.

Further Analyses

We conducted further analyses to obtain additional insights for the pattern of results obtained above. The goal of these analyses was to explore the actual outcomes experienced by the IT professionals who switched jobs. First, we explored the changes in job status when IT professionals moved to alternative jobs. IT professionals may increase/maintain job status by moving to managerial and professional jobs. Alternatively, job status may decline when moving down to jobs in occupations such as clerical, sales, technician, craft, production, and food service. Changes in job status were analyzed by evaluating relative proportions of upward or downward movement, using a chi-square test for significance.

Second, we examined whether job mobility "pays off" in terms of pay level and relative pay gap. We conducted a multivariate analysis of covariance to examine changes in the marginal means of real pay and relative pay gap before and after job mobility, controlling for the same covariates as in our Cox regression. These analyses were conducted separately for IT males and IT females.

IT Males

Job Status. Analyses of job status indicate significant differences across the types of job mobility ($\chi^2 = 553.33$, df $= 3$, $p < 0.001$). All IT males increase or maintain their job status by staying in their current position (100%) or by turning over to another IT job in another company (100%). By contrast, 59% of IT males increase or maintain their job status when they turnaway-within, and 43% of IT males increase or maintain their job status when they move to a non-IT job in another firm (turnaway-between).

Real Pay and Relative Pay. The multivariate test ($F_{(3,3,330)} = 4.029$, $p < 0.010$) indicates significant differences in the change in real hourly pay across types of job mobility. IT males increase real hourly pay more by staying in their current IT jobs (*Mean change*, 5.47%; $p < 0.001$) or by turning over to another IT position in another firm (*Mean change*, 8.01%; $p < 0.001$). There is no significant increase in real pay by turning away-within (*Mean change*, 1.28%; $p > 0.10$) or by turning away-between (*Mean change*, 3.30%; $p > 0.10$).

The multivariate test, however, found no significant differences in the change in relative pay gap ($F_{(3,3,330)} = 0.68$, $p > 0.10$) across the types of job mobility for IT males. The results indicate that changes in relative pay gap do not significantly differ across turnover, turnaway-within, and turnaway-between.

IT Females

Job Status. Analysis of job status indicates significant differences across the types of job mobility ($\chi^2 = 576.77$, df $= 3$, $p < 0.001$) for IT females. Consistent with the pattern for IT males, almost all IT females maintain their job status by staying in their existing IT positions (100%) or by turning over to another IT position in another company (99%). By contrast, 48% of IT females increase or maintain their job status when turning away-within to a non-IT job, and 38% increase or maintain their job status when turning away-between.

Real Pay and Relative Pay. The multivariate test ($F_{(3,2,836)} = 2.648$, $p < 0.050$) indicates significant differences in the change in real hourly pay across the types of job mobility. IT females significantly increase real hourly pay by staying in their current IT positions (*Mean change*, 4.50%; $p < 0.01$), and marginally increase real hourly pay by turning over (*Mean change*, 6.38%; $p < 0.10$). There is no significant change in real pay by turning away-within (*Mean change*, 2.74%; $p > 0.10$) or by turning away-between (*Mean change*, −1.41%; $p > 0.10$). This pattern of findings is consistent with that of IT males.

Unlike for IT males, the multivariate test for IT females indicates significant differences in changes in relative pay gap ($F_{(3,2,836)} = 15.673$, $p < 0.001$) across the types of job mobility. Relative pay gap narrows significantly when IT females turnaway-within (*Mean change*, −31.79%; $p < 0.001$) or turnaway-between (*Mean change*, −29.64%; $p < 0.001$). The relative pay gap does not change when IT females turn over or remain in their current IT jobs.

Discussion

This study examines the relationship between relative pay gap and three forms of job mobility for IT professionals. The three forms of job mobility are (1) turnover, i.e., moving to another IT job in a different firm; (2) turnaway-within, i.e., moving to a non-IT job in the same firm; and (3) turnaway-between, i.e., moving to a non-IT job in a different firm. Overall, the results are consistent with the predictions of distributive justice. A relative pay gap is shown to be positively and significantly associated with the likelihood of job moves by IT professionals. Because distributive justice theory is silent about the destinations of job mobility, we incorporated theories of human capital specificity and stigmatization to develop a set of more nuanced, gender-specific explanations of the focal relationships.

Human capital theory predicts that, ceteris paribus, IT professionals investing in IT-specific and not easily transferable skills will be more likely to turn over than turn away-within, and more likely to turn away-within than turn away-between. Turnover should be the most likely job mobility to leverage on occupational skill specificity. Turnaway-within should be the next more likely job move to leverage on organizational skill specificity. Turnaway-between should be the least likely option, because neither existing occupational or organizational skills can be leveraged.

Therefore, our second set of hypotheses propose that the larger the relative pay gap, the higher the likelihood of turnover than turnaway-within or turnaway-between. However, we posit that these predictions occur only for IT males. For IT females, given the added gender-based stigmatization in the IT profession, we expect that IT females will more likely turn away from the IT profession altogether (either to a non-IT job within the same firm or in a different firm) than to move to another IT job in another firm (turnover). Hence, we proposed in our third set of hypotheses that the larger the relative pay gap, the more likely it is that IT females will turn away-within than turn away-between, and turn away-between than turn over.

IT Males

Consistent with the human specificity arguments (Hypotheses 2B and 2C), we find that IT males are more likely to turn over than turn away-between, and to turn away-within than to turn away-between. However, contrary to our expectations (Hypothesis 2A), IT males are more likely to "seed the line" by turning away-within a firm rather than turning over to another IT position in another firm.

This surprising finding suggests that the ubiquity of IT in non-IT jobs may have eased the movement of IT males from IT to non-IT line positions. Furthermore, because turnaway-within tends to occur at the discretion of the firm (Reich and Kaarst-Brown 1999), turnaway-within may signal the IT professional's value to a non-IT position in that firm (Bangerter et al. 2012). Firms may move IT professionals to non-IT jobs (i.e., "seeding the line") to reap competitive advantages from having IT-trained employees with deep firm-specific human capital (Reich and Kaarst-Brown 1999). "Seeding the line" tends to increase the sharing of information and understanding of a firm's processes and capabilities, and break down barriers that often inhibit within-firm learning (Nembhard and Tucker 2011).

In essence, the firm retains and makes explicit knowledge and skills that were otherwise internal to individuals and/or departments (Flores et al. 2012). The relative ease of movement from IT to non-IT jobs may also explain why some IT males turn away-between even though such a job move is the most costly and least likely.

Our further analyses of the "outcomes" experienced by IT males after they make a job move show that IT males suffer a drop in job status and forgo higher pay when they move to a non-IT job, whether in the same firm or in another firm. However, moves into and out of IT do not significantly impact relative pay gaps for IT males.

IT Females

The patterns of mobility for IT females are consistent with our a priori stigmatization arguments (Hypotheses 3A and 3B). We find that relative pay gap is associated with the higher likelihood that IT females turn away (within or between) than turn over. As expected, turnover is IT females' least likely type of job mobility in relation to a relative pay gap. For IT females, our results suggest that stigmatization may have a greater influence compared to human capital specificity considerations to the extent that IT females prefer to "seed the line" within the same firm or with another firm than to move to another IT job.

We note that, similar to IT males, some IT females do "seed the line" by turning away-within a firm to non-IT jobs. These IT females move into non-IT professional positions in functions such as human resources and finance or to non-IT general management and administration jobs. Turning away-within a firm is likely to protect ex-IT females' returns to firm-specific human capital, because it signals an employee's value to the firm. Some IT females also sought alternative jobs in the external labor market by turning away-between.

Disconfirming Hypothesis 3C, IT females are equally likely to turn away from IT jobs within the same firm as to a different firm. We suspect that IT females may turn away-between because either they are not offered a line job by their current firm or they wish to leave their current firm to avoid a potential spillover of stigma to line jobs within the same firm (Kulik et al. 2007, Triana 2011).

Turning away-within a firm may confirm and reinforce the stereotype that females are suited for less technically oriented work compared to males (Serva 1994). IT females may be offered jobs that are labeled as "feminine" and viewed as requiring less overall human capital compared to jobs labeled as "masculine" (Gorman 2005, Ridgeway 1997). Jobs labeled as "feminine" are often lower in status and pay (Kalev 2009, Reskin 1988). Furthermore, females may also be stereotyped as holding less human capital than required for a job because of specific efforts targeted at filling vacant job roles with workers of a demographic group (Heilman et al. 2004). Hence, the returns to IT females' firm-specific human capital may be discounted in other non-IT jobs within their current firm. The discounting of both IT-specific and firm-specific human capital lowers costs associated with turnaway-between, thus making turnaway-between as viable as turnaway-within.

Additional analysis of the "outcomes" experienced by IT females after job moves reveals that, similar to IT males, remaining in their current IT job or turning over to another IT job in another firm would significantly increase their real pay. However, neither strategy narrows relative pay gaps as much as turnaway-within and turnaway-between. Indeed, by leaving the IT profession, IT females may be able to restore pay equity. This may also substantiate why IT females are least likely to turn over in light of a relative pay gap.

However, IT females appear to experience a decline in job status, as the jobs to which they move tend to be clerical, food service, sales, and production-type jobs. Jobs in such occupations are often lower in status (Hauser 1998) compared to IT jobs. The clerical, food, and sales jobs also tend to be gender balanced or female dominated (Budig 2002). Stigmatization of females through pay differentials has been shown to be less likely in gender-balanced and female-dominated occupations (Budig 2002, England et al. 2007). The low probability of stigmatization in gender-balanced and female-dominated occupations may explain why IT females' real pay levels were similar to those in their previous IT jobs.

Conclusion

This study, to the best of our knowledge, is the first to examine how relative pay gap is related to job mobility for IT professionals. Specifically, this study examined the association between relative pay gap and three distinct types of job mobility: turnover, turnaway-within, and turnaway-between. The results show that larger relative pay gaps are significantly associated with IT professionals' likelihood of making job moves. Furthermore, our findings indicate that IT males and IT females differ in the likelihood of turnover, turnaway-within, and turnaway-between, given a relative pay gap. In the following sections, we note important theoretical contributions and implications of our study, discuss the practical implications, and identify the limitations of the study and areas for future research.

Theoretical Contributions and Implications

We identify three theoretical contributions associated with this study. First, this study demonstrates the importance of conceptualizing and operationalizing job mobility as a multifaceted construct. Instead of simply treating job mobility as a phenomenon of leaving one's current position, we show that job mobility is more complex when we consider individuals' job destinations. By doing so, our study represents an important extension to current theories of job mobility and turnover. It specifically addresses calls in the turnover literature (e.g., Joseph et al. 2012, Kirschenbaum and Weisberg 2002) to verify whether individuals actually move to similar jobs in other firms.

In addition, refining the concept of job mobility is important because, as this study shows, we are able to discover gender-related nuances in the job mobility patterns of IT professionals. Had we not examined job mobility in a multifaceted manner, we would not have discovered that IT females are more likely to leave the IT profession when changing jobs in relation to a relative pay gap. With a refined and multifaceted conceptualization of job mobility, future research could spawn more sophisticated and differentiated nomological networks around different models of job mobility. In that way, it would be possible to study and develop refined explanations that truly reflect actual and complex workplace phenomena.

The second theoretical implication of our study concerns the importance of pay, specifically, the importance of a relative pay gap, in influencing job mobility. Prior research on IT turnover and job mobility has focused on sociopsychological factors of turnover, such as job satisfaction, perceived job alternatives, role ambiguity, and role conflict (see, for example, the meta-analysis by Joseph et al. 2007). This study reintroduces the importance of a hygiene factor—pay—and its potential effects on job mobility. We found that larger relative pay gaps were significantly associated with the likelihood of making job moves.

Moreover, our findings show that the effects of relative pay gap on job mobility are not homogeneous across all IT professionals. IT females appear to increase their job status and pay levels when making moves within the IT profession, but seem unable to reduce relative pay gaps. IT females appear to restore pay equity only by leaving the IT profession and at the expense of lowering job status and pay levels. As such, the job moves of IT females suggest that they seem to favor receiving equitable pay, even if the job move means a decline in job status and pay level. Like IT females, IT males are able to increase job status and pay levels when moving to jobs within the IT profession, but not when moving to jobs outside the IT profession. In contrast to IT females, IT males do not reduce relative pay gaps when moving to jobs outside the IT profession. Little is known about how IT professionals are able to increase both job status and pay level and reduce relative pay gaps when making job moves. Little is also known about why IT females appear to weigh pay equity more than job status or level of pay in their job move behaviors. Future research could examine more closely the sociopsychological mechanisms associated with the alternative forms of job mobility across genders in relation to pay equity.

Third, findings of this study have theoretical implications for how IT human capital is conceptualized. In our theoretical development, we categorized IT human capital as a type of specific human capital that is unique to the IT profession. Recall that specific human capital, as contrasted with general human capital, is defined as unique and not easily transferred across other domains. Yet, our study suggests that, both males and females can leave the IT profession to "seed the line," perhaps because of the ubiquitous deployment of IT in firms. Such ease of movement of IT professionals to jobs outside of the IT profession suggests that IT skills, unlike other professional skills (e.g., medicine, law, or accounting), may be more easily transferable than previously thought.

In effect, it may thus be more appropriate to treat IT human capital as likely having both some general and specific components. Future research could distinguish the kinds of IT skill sets that allow an IT professional to seed the line easily from those that do not. For example, perhaps an IT professional who is more entrenched in IT infrastructure is less likely to transfer his or her IT skills than one who has systems analysis skills that may more readily be applied to other jobs.

Implications for Practice

For practice, our findings imply that managers should focus attention on the importance of pay, especially relative pay. The results reported here show that

IT professionals (both males and females) will leave the IT profession given relative pay gaps. We find that a 10% increase in relative pay gap increases the likelihood of IT males' job mobility, controlling for covariates, by 4.67%, turnover by 3.90%, turnaway-within by 9.35%, and turnaway-between by 2.47%. In turn, we find that a 10% increase in relative pay gap increases the likelihood of IT females' job mobility, controlling for covariates, by 5.44%, turnover by 4.14%, turnaway-within by 7.37%, and turnaway-between by 8.80%. Firms that compensate IT professionals inequitably may find it difficult to retain IT talent. The loss of talent is doubled when firms are unable to retain female IT talent. First, firms may lose talent that may be equal to or better than the average male IT talent. Second, firms lose IT-specific and firm-specific human capital that would otherwise increase their effectiveness and efficiency.

Our results also imply that managers in charge of compensation should continue to be vigilant. Because "laws alone do not remedy the gender (pay) gap" (Vogt 2008, p. 338), managers must continue to emphasize pay policies based on meritocracy or risk attrition of talent (Blau and Kahn 2003). A relative pay gap persists despite monitoring and enforcement of equal employment opportunity laws. Estimates using Current Population Survey data indicate a widening relative pay gap between IT females and IT males from 9% in 1997 to 19% in 2003, controlling for human capital, job, and organizational characteristics (Levina and Xin 2007). The Bureau of Labor Statistics (2013b) estimates a relative pay gap of between 12% to 27% in the median pay of IT males and females across IT jobs in the U.S. IT workforce.

The ubiquity of IT across different functional areas of a firm creates a boon for IT professionals and a bane for managers tasked to retain IT professionals. The ubiquity of IT facilitates ease of movement out of the IT profession (Reich and Kaarst-Brown 2003). This ease of movement, coupled with a relative pay gap, suggests that the IT profession will continue to face persistent labor imbalances and also a gender imbalance.

Whereas IT males are most likely to stay within their firm or turn over to another IT position even if they change firms, the study finds that IT females are most likely to turn away from the IT profession to close the relative pay gap. This finding suggests that potential solutions to attract and retain IT females in the IT profession may need to be quite different, and that a "one size fits all" approach may not work for both IT males and females.

Limitations and Future Research

The NLSY79 contains detailed work histories that enabled us to examine the origins and destinations of job mobility. Its longitudinal nature allowed us to examine the relative pay gap and its consequences. We are unaware of any other study in the IT or management literature examining the relationship between relative pay and job mobility over a similar length of time. However, as with any empirical study, there are constraints in the data.

First, job mobility beyond 2006 remains unobserved. The right censoring of our data is an opportunity for future research to examine relative pay gap and job mobility toward the end of IT professionals' careers. Respondents in our data set are between 41 and 48 years old (as of 2006). The extant literature (e.g., Joseph et al. 2012) suggests that the frequency of job mobility should decrease with tenure and age. It would be interesting to examine whether results reported here are attenuated with tenure and age.

Second, with the exception of job satisfaction (which is captured in the NLSY79), we were not able to examine subjective experiences and motivations associated with relative pay. For example, no direct measures of pay equity (or inequity) perceptions were examined because the NLSY79 data do not contain such perceptual measures. Even so, the behavioral manifestations reported in this study are consistent with the central tenets of pay equity theories. The results reported here are also consistent with results in labor economics and human resource management that use psychological theories to explain and predict such relationships using objective measures. Nonetheless, future research should draw on primary data collection methods to corroborate and complement this study by probing more deeply into the subjective attitudes and perceptions of both IT females and IT males.

Third, future research should examine other potential explanations for the differences in job mobility patterns of IT males and IT females. Prior research has highlighted that IT males and IT females have different experiences in the IT work environment or might experience the IT work environment differently (e.g., Reid et al. 2010, Trauth et al. 2009). IT males and IT females also differ in the dispositions to move (e.g., Adya 2008, Ahuja 2002). These differences could contribute to different job mobility patterns. Another factor that might be examined is whether IT professionals have a greater desire to move than non-IT professionals, i.e., whether there is a "turnover culture" in IT (Moore and Burke 2002).

The findings reported in this study underscore the theoretical and practical importance of IT professionals' career-related actions associated with relative pay. Our study suggests that future research should adopt a nuanced explanation for IT professionals' career-related behaviors. Such explanations may require the use of multiple theoretical lenses. Our study also suggests that relative pay gap should be an important component in the effort to retain IT professionals within firms and the IT profession. Failure to address a relative pay gap may adversely affect the productivity of the firm and the level of diversity within the IT profession.

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Dedication
This paper is dedicated to the late Dr. Sandra Slaughter.

May her

Spirit of Learning;
Joy in Research; +
Dedication to Science

live forever in our hearts and minds.

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