The enablers of early career outcomes of information technology professionals

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The Enablers of Early Career Outcomes of Information Technology Professionals

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Abstract

The sustainability of digital economies requires that IT prospects find employment, persist and succeed in IT careers. IT research have yet to examine the enablers of these salient early career outcomes. Rather, the earlier studies have largely focused attention on the enablers of career outcomes related to mid to late career IT professionals. The insights proffered by the earlier studies fail to adequately explain the enablers of initial IT employment, early IT career persistence and success in terms accrued wages. This dissertation therefore begins a research agenda that extends the narrative of the extant research and focuses extensively on early career IT professionals. In doing so, I conduct two studies.

Essay 1 focuses on college IT graduates by examining how college-based career interventions influence initial IT employment and career persistence. Drawing largely on the human capital literature, I formulate a set of hypotheses that relates high and low direct experiences gained from college-based career interventions to (1) the likelihood of initial IT employment and (2) IT career persistence. Results indicate that cooperative education, internship and mentorship experiences increase the likelihood of initial IT employment success. Further, I find that internship and mentorship experiences are strongly related to career persistence.

Essay 2 focuses on early IT career success by asking whether IT graduates have more successful careers, in terms of accrued wages, compared

to non-IT graduates who pursue IT careers. I synthesize arguments flowing from the human capital and the job-skills matching literatures and build a theoretical model that compares the wages of IT and non-IT graduates in IT careers. I find that IT degrees command higher wages than non-IT degrees.

CHAPTER 1

Research Aim

The current dissertation asks the broader research question: how do college-based career interventions and formal IT education impact early career outcomes? In answering this research question I conduct two research studies. The two studies or essays are collectively aimed at extending our understanding of the factors that enable career outcomes in early IT careers.

Together, the two essays accord well with existing studies about IT career outcomes including employability, career mobility and objective career success. This dissertation, however, differs from the existing studies that examine the enablers of IT career outcomes in the following way.

The current dissertation examines the enablers of early IT career outcomes as opposed to the enablers of career outcomes pertinent to mid to late career IT professionals, which has received considerable scholarly attention. I focus attention on early IT careers to bring a fuller understanding to the factors that facilitate graduate initial IT employment, persistence in IT careers and achievement of early career success in terms of wages.

Motivation and Research Question

The pervasiveness of digital technologies in modern economies has raised the demand for skilled information technology (IT) professionals. IT professionals are knowledge workers who occupy IT job roles including systems analysts and administrators, computer programmers and support specialists and computer and information systems managers (OECD, 2016; US

Bureau of Labor Statistics, 2015a). The United States (US) Bureau of Labor Statistics (BLS) projects an increase from 3.9 million to 4.4 million IT jobs from 2014 to 2024 (US Bureau of Labor Statistics, 2015a). Meeting the demand for skilled IT labor is essential for the sustainability of digital economies. The demand for skilled IT labor, if not met, will ultimately reduce the innovative capacities and competitive advantage of digital economies.

Colleges are a sustainable source of labor supply and remain vital in meeting the demand for IT labor. Yet the number of IT graduates who enter IT employment and thereafter persist in IT careers remains a concern. Evidence suggests that 32% of US IT graduates do not enter IT employment after graduation (Salzman, Kuehn, & Lowell, 2013). Even for those who enter IT employment after graduation, an estimated 50% leave the IT profession in the early career stages (Salzman et al., 2013). IT research has attributed the employment problem and attrition of IT graduates from the IT workforce to inadequate practical training and weak socialization in undergraduate IT programs (Joseph, 2008). The attrition problem is hardly confined to the US. It is a transnational phenomenon, an albatross around the neck of many developed economies (Pinxten, De Laet, Van Soom, & Langie, 2015).

The relatively high number of IT graduates who do not enter IT employment and persist in IT careers has led to concerted efforts toward designing and implementing a host of experiential learning programs (college-based career interventions) with the aim of improving graduate employability and persistence in IT careers (Church, 2010; Fifolt & Searby, 2010; Wilson et

al., 2012). Yet IT literature is silent on the consequences of such career interventions. There is little scientific inquiry examining the role played by college-based career interventions in initial IT employment and career persistence.

Interestingly, the attrition of IT graduates from the IT workforce and the increasing demand for IT labor have inadvertently created employment opportunities for non-IT graduates. Pursuing IT careers is no longer an endeavor restricted to only full-blown computer and information science graduates. Non-IT graduates are now able to travel down similar career paths (Cisco Systems Inc., 2008; Joseph, Boh, Ang, & Slaughter, 2012). Indeed, a recent survey that polled over 26000 IT professionals from 157 countries revealed that nearly half attained no form of IT degree (InfoWorld, 2015). The increase in the supply of IT labor from nontraditional sources is often attributed to the widespread democratization of the internet and online learning resources, which has empowered individuals to learn employable IT skills (Turkle, 2005; Warren Harrison, 2004).

The supply of IT talents from nontraditional sources has raised important questions in regards to the value of IT degrees. The question of whether IT graduates have more successful careers in terms of accrued wages, relative to non-IT graduates, opens an avenue for further inquiry. The question becomes even more relevant for IT professionals in the early career stage when they have limited working experience in IT and college education is envisaged to have the greatest influence on career success.

Essentially, a research agenda that shifts the narrative of the extant research, which has focused much attention on mid to late career IT professionals, to early career IT professionals is particularly relevant and timely. In this dissertation, I begin a research agenda that focuses extensively on the enablers of career outcomes and asks the broader question: *How do career interventions and formal IT education enable salient outcomes in the early stages of IT careers?*

Career-Stage Differentiation

Scholarship on careers remains an enduring endeavor. Career theorists and empiricists from diverse fields of study including sociology, human resource management and social psychology have examined issues related to career development and progression, career outcomes and their antecedents (Arthur, Hall, & Lawrence, 1989; Noe, 1996; Adler & Adler, 2005; Super & Hall, 1978). The early studies on careers draw on theoretical perspectives that conceptualize careers as sequences of occupations, progressing through episodic stages rather than continuous (Super, 1957, 1990).

This traditional conception of careers as a series of episodic stages is akin to tenets of life theories. Life theories crystallize around the view that as individuals age they encounter different experiences and challenges at the early, middle and late stages of their lives (Hall, 1976; Levinson, 1978). Inspired by this, most studies examine career phenomena across the early and mid to late stages of the career cycle (Super, 1957, 1990; Wang, Olson, & Shultz, 2012).

The early career stage is usually explorative (Super, 1957). It comprises of young individuals who are entering the workforce for the first time. Individuals in their early careers take a profound interest in examining the career path they aspire to chart. They continuously assess whether they must change jobs or careers to meet their needs and aspirations (Cohen, 1991; Super, 1957; Wang et al., 2012). For this reason, early career professionals have lower levels of career embeddedness – the extent to which an individual is attached to a specific occupation often determined by a combination of forces such as person – occupation fit, social capital or links and sacrifice (Feldman & Ng, 2007; Mitchell, Holtom, Lee, Sablinski, & Erez, 2001; Ng & Feldman, 2007).

Another line of inquiry into early careers focuses on occupation-specific experiences. Dyrbye et al. (2014) analyzed the burnout rates of some 10,000 early career physicians and found that medical trainees and early career physicians reported higher levels of burnout rates than the national average. The prevalence of burnout in the early stages of medical careers is partly attributed to the lower level of social support, high uncertainty and environmental challenges associated with starting a new practice and career (Dyrbye et al., 2014; Shanafelt et al., 2009, 2012). Other studies that sample teachers and nurses corroborate the finding that early career professional workers experience higher levels of stress, anxiety and burnout (Billingsley, Carlson, & Klein, 2004; Rudman & Gustavsson, 2011).

The differences in the cognitive experiences of early career professionals and mid to late career professionals is well documented (Wang et

al., 2012). The most striking difference perhaps is related to how they attend to career role models. Mid to late career professionals tend to focus attention on the negative behaviors and personal attributes of their role models in an effort to refine, enhance and reaffirm their self-concept (Gibson, 2003). In contrast, early career professionals focus attention on the positive behaviors and attributes of their role models (Gibson, 2003). This motivates them to create a viable self-concept which is vital for the development of professionals skills and attributes that are necessary for successful transitions into mid to late careers (Gibson, 2003).

The concept of career success has been differentiated across the early and mid to late career stages. The literature reveals that indicators such as gender and mentoring experience play influential roles in deciding early career promotions, compensation and career satisfaction levels (Cox & Harquail, 1991; Whitely & Coetsier, 1993). Gender differences in wage expectations result in disparate levels of compensations, with female professionals negotiating for lower salaries than their male counterparts (Cox & Harquail, 1991). Men tend to have higher expectations of their salaries in the early career stage (Tromski & Subich, 1990).

Human capital endowment differentiates early career professionals from mid to late career professionals in regards to career success (Wang et al., 2012). Unlike early career professionals, mid to late career professionals are often well endowed with professional as well as organizational experience which proves valuable to employers (Becker, 1975; Lam, Ng, & Feldman, 2012). It is well

documented that professional and organizational experience predict objective career success including compensation and promotions (Tesluk & Jacobs, 1998; Wang et al., 2012).

Mid to late career professionals typically assess career success by accounting for the level of psychological involvement with a career. They ascribe indicators such as career satisfaction, affective professional commitment and career attachment to career success (Erdheim, Wang, & Zickar, 2006; Mathieu & Zajac, 1990). Mid to late career professionals tend to report higher levels of commitment and satisfaction with their careers than early career professionals (Erdheim et al., 2006; Mathieu & Zajac, 1990). The higher levels of career satisfaction and commitment reported by mid to late career professionals reflect in their mobility patterns. Mid to late career professionals are less likely to switch employers and occupations (Wang et al., 2012).

In conclusion, the experiences, human capital endowment and job attitudes of mid to late career professionals that prompt career outcomes appear to be qualitatively and quantitatively different from that of early career professionals. The differences reflect the conceptual distinction between the early and mid to late career stages. I argue that conceptually desegregating the early stage of careers from mid to late careers provides a richer context that refines our understanding of the experiences, attitudes, behaviors and human capital endowment of early career professionals.

IT Career Outcomes

In a similar fashion, information system (IS) scholars have taken a keen interest in IT careers over the last couple of decades, resulting in two dominant streams: career transitions and career success. The first stream, career transitions, emerged in response to the recurring employee mobility and stability challenges that afflicted the IT labor market (Ginzberg & Baroudi, 1988; Joseph, Ang, & Slaughter, 2015; Joseph et al., 2012; Young, 2000).

In the early 1970s to 1990s the IT labor market witnessed a chronic shortage in IT labor supply (Joseph, 2006). The shortage in IT labor supply was aggravated by the increase in IT outsourcing and offshoring activities. It was therefore imperative to investigate what the consequences were for IT professionals and what career options they pursued i.e. whether they continued to pursue IT careers by joining the outsourcing vendor firms or abandoning IT and moving into line functions and non-IT jobs within the incumbent firms.

Traditionally, IT careers have been considered as comprising of two distinct paths: technical and managerial paths (Ginzberg & Baroudi, 1988). This thinking was consistent with the concept of “The Organization Man”, which emphasizes upward mobility in organizations (Whyte, 1956, 2002). The introduction of the concept of “boundaryless” careers into the career’s literature, however, has inspired researchers to reconsider the traditional view of a dual IT career path (Arthur & Rousseau, 2001).

By analysing a sample of 500 IT professionals drawn from the National Longitudinal Survey of Youth 1979 cohort, Joseph et al. (2012) discovered a

new IT career typology comprising of three distinct career paths: IT careers, Professional Labor Market (PLM) and Secondary Labor Market (SLM). Individuals in IT careers hold IT jobs throughout their careers, whereas individuals who ply the PLM path leave IT for high-status jobs usually within the same organization. Individuals in SLM careers have a short stint or tenure in IT before moving into low-tier jobs, which offer lower status and opportunities for promotions, usually within the same organization.

The occupational mobility pattern that characterize PLM and SLM careers is consistent with prior research on IT mobility (Lee, 2005; Reich & Kaarst-Brown, 1999, 2003). Organizations move mid to late career IT professionals into permanent non-IT jobs to “seed the line” (Reich & Kaarst-Brown, 1999). The purpose of seeding the line is to leverage the experience and expertise of mid to late career IT professionals. Seeding the line aims to improve the business areas or line functions of the organization where technology still remains core (Reich & Kaarst-Brown, 1999).

By seeding the line, mid to late career IT professionals serve as conduits through which knowledge about the organization’s IT capabilities is disseminated to co-workers in non-technical roles (Reich & Kaarst-Brown, 2003). In essence, experience in IT plays an enabling role in switching to non-IT careers or pursuing non-IT roles. This is a possible explanation for the lower levels of career persistence of some IT professionals in the mid to late career stage (Joseph et al., 2012).

The second stream of research, career success, largely examines IT human capital attributes as determinants of objective career success (e.g. IT compensations, IT salaries, IT wages and employability) (Ang, Slaughter, & Ng, 2002; Joseph et al., 2012; Levina & Xin, 2007; Mithas & Krishnan, 2008). The consensus is that IT-specific human capital – human capital unique to the IT profession and not readily transferable across occupations – is the coin of the realm of the profession (Ang, Slaughter, & Ng, 2002).

Human capital accumulated over the course of IT work increases productivity, which proves valuable to IT employers. IT professionals who remain in IT careers and accumulate IT-specific human capital, improve their employability prospects and command higher wages (Ang, Slaughter, & Ng, 2002; Lee, Trauth, & Farwell, 1995; Mithas & Krishnan, 2008).

Early IT Career Outcomes

The studies (e.g. Ang et al., 2002; Levina & Xin, 2007; Mithas & Krishnan, 2008) that constitute the two streams of research on IT careers have been limited to samples of mid to late career IT professionals. As shown in Table 1, Ang et al. (2002), Levina and Xin (2007) and Mithas and Krishnan (2008) use samples of IT professionals who have an average work experience of 7.0 years (SD = 5.7), 15.9 years (SD = 8.85) and 18.0 years (SD = 9.0) respectively.

Table 1: Average IT Experience (Years) of Study Sample

	Mean	SD
Mithas & Krishnan (2007)	18.07	9.00
Ang et al. (2002)	7.03	5.73
Joseph et al. (2012)	10.80	6.60
Levina & Xin (2007)	15.94	8.85
Slaughter, Ang & Boh (2007)	6.32	6.56

The sampling of mid to late career IT professionals has influenced theorizing and our thinking of how quantitative experience variables impact IT career outcomes much to the neglect of qualitative experiences such as career interventions and a formal education in IT. For example, the thesis that higher levels of IT and firm experience influence employment outcomes and career success is informed by the lopsided sampling of mid to late career IT professionals (Ang, Slaughter, & Ng, 2002; Levina & Xin, 2007; Mithas & Krishnan, 2008). The thesis may be different if one considers and examines a sample of early career IT professionals.

It is important to extend the sample to include early career IT professionals for the following reason. As earlier articulated under the section on “The Concept of Career Stage Differentiation”, early and mid to late career professionals differ in the levels of human capital endowment, career experiences, work attitudes and behaviors. IT professionals in the early career stage are not well endowed with work experience that determine employment and career success.

The antecedents of early IT career outcomes including initial IT employment, persistence in IT careers and success in early IT careers remain

understudied, leaving a gap in the literature. This gap has created an incomplete view of the nomological network on IT career outcomes. A research agenda that focuses on early career IT professionals could unearth new theoretical narratives that complement the existing research that has focused on samples of mid to late career IT professionals.

Research Agenda

This dissertation examines the enablers of early IT career outcomes. Figure 1 presents a description of the research question, theory and methodology employed in each study. Essay 1, “*College-to-Work Transition: Raising IT Employability and Persistence in Early Careers of IT Professionals*”, focuses on college to IT work transition. Specifically, Essay 1 addresses two questions: How do career interventions determine (1) initial IT employment and (2) early IT career persistence?

To answer question 1, I draw on human capital theory (Becker, 1975), which predicts that investments in human capital attributes result in favorable employment outcomes. I develop a theoretical model linking participation in college-based career interventions to the likelihood of securing an IT job at graduation. I draw a sample of IT graduates from the NLSY97 data, track their working histories and test the theoretical model using parametric survival modelling.

I answer question 2 by synthesizing the literature on human capital (Becker, 1975) with identity theory (Callero, 1985; Stryker, 1980; Turner, 1978). The thesis is that career interventions are foster the development of

professional identities. A salient professional identity reinforces attachment behaviors toward the profession. Using data drawn from the NLSY97 survey, I test the set of hypotheses linking career interventions with IT career persistence using a Tobit panel regression analysis.

Essay 2, “*An Empirical Examination of the Value of Formal IT-Oriented Degrees*” inquires whether IT degrees command a higher wage premium in early IT careers. The study draws on the tenets of human capital specificity (Becker, 1975) and concepts from the skills matching literature (Robst, 2007; Sattinger, 1993), which suggests that productivity is maximized when an individual’s stock of human capital is optimally matched with the skills requirements of a job. I build a theoretical model that compares the wages of IT graduates with non-IT graduates. Using a sample of IT professionals in their early career stages obtained from the NLSY97 data, I test the theoretical model using a linear mixed effects model.

In summary, the two essays that constitute this dissertation seek to provide theoretical insights about the enablers of salient early career outcomes – i.e. initial IT employment, IT career persistence and early career success. In doing so, the dissertation contributes to the two streams of IT career research i.e. career transitions and career success. Specifically, I extend the existing theoretical narrative, which is mostly informative of the attitudes, behaviors and intentions of IT professional in their mid-to late career stages, to include new theoretical perspectives and antecedents of early career outcomes.

Figure 1: Theoretical Overview of the Research Agenda

CHAPTER 2

College-Based Career Interventions: Raising IT Employability and Persistence in Early Careers of IT Professionals

Introduction

For most digital economies, the bulk of the demand for information technology (IT) professionals is traditionally met by graduating college IT majors. However, in the US 50% of IT-oriented graduates including computer science and computer engineering graduates do not enter IT employment after graduation (Salzman et al., 2013). Even for the graduates who enter IT employment, 29.4% exit within the first two years of entry or fail to persist in early IT careers (Joseph et al., 2012).

With the increasing demand for IT labor (US Bureau of Labor Statistics, 2015a), the initial employment and early career persistence problem in IT could lead to a labor crunch. An IT labor crunch hamstrings the capacities of digital economies to innovate (Atkinson & Mayo, 2010; PCAST, 2012).

IS researchers contend that IT graduates are constrained by a lack of adequate work experience and weak socialization into IT careers (Chen, 2013; Lee, Koh, Yen, & Tang, 2002), which could explain the initial employment and persistence problem. To ostensibly improve the initial employment and persistence problem, there have been widespread implementations of career interventions in colleges (Choudhury, Lopes, & Arthur, 2010; Church, 2010; Fifolt & Searby, 2010; STWOA, 1994; Wilson et al., 2012). Yet while scholars

agree that career interventions matter in facilitating better career outcomes (Narayanan, Olk, & Fukami, 2010), there is little systematic research that has explored the relationship between college-based career interventions and initial employment, and IT career persistence.

Few studies from the skills development literature (Aasheim, Li, & Williams, 2009; Dillon & Lending, 2014; Trauth, Farwell, & Lee, 1993) and turnaway research (Joseph, Ang, & Slaughter, 2015) offer important insights into career interventions, initial employment and IT career persistence. Dillon and Lending (2014) found that 70% of college IT students who are mentored by seasoned IT professionals find employment at graduation. Trauth et al. (1993) argue that mentorship and internship programs presumably bridge the IT skills gap that exists between academic training and the dynamic IT industry. College-based career interventions prepare participants with productive hands-on experience (Narayanan et al., 2010).

The findings from the IT skills development literature (Aasheim et al., 2009; Dillon & Lending, 2014; Trauth et al., 1993) provide evidence and reasons for the favorable outcomes of career interventions. However, the studies (e.g. Dillon & Lending, 2014; Trauth et al., 1993) remain largely descriptive and the findings could suffer from self-selection or endogeneity bias. Unobserved heterogeneity could influence both individual participation in career interventions and the likelihood of securing initial IT employment.

Turnaway research investigates why IT professionals exit or fail to persist in IT careers. It is well documented that relative pay gap is associated

with the likelihood of exiting the IT profession i.e. reduced levels of IT career persistence (Joseph, Ang, & Slaughter, 2015). The finding is attributed to the predictions of distributive justice theory (Folger & Konovsky, 1989). Distributive justice theory posits that when pay received is lower than a comparable other, there is a withdrawal action to restore the inequity.

However, IT graduates are less likely to experience relative pay gaps in early careers. This is because they share comparable human capital profiles. The theoretical arguments flowing from the distributive justice literature are not sufficient in explaining persistence in early IT careers, leaving a gap in the IT turnaway research. So why do some IT graduates persist in early careers and others do not?

The methodological and theoretical limitations of the studies in the IT skills development literature and turnaway research culminate in the need to systematically reexamine career interventions in IT. I examine the links between: (1) college-based career interventions and initial IT employment and (2) college-based career interventions and IT career persistence. By doing so, the current research contributes to the literature on IT skills development and turnaway research in the following ways.

First, going beyond the descriptive study of career intervention outcomes, the current research develops a theoretical model that links experiences gained from college-based career interventions to initial IT employment. In addition, the current research draws on social and experiential learning literatures (Bandura & Walters, 1977; Herr & Watts, 1988) to frame

experiences gained from career interventions as high and low direct experiences. The two modalities of experience gained from career interventions refine our understanding of how different career interventions relate to career outcomes.

Second, this research departs from the considerable studies that have examined proximal outcomes of career interventions including career skills acquisition and initial employment (see Narayanan et al., 2010). In addition to examining a proximal outcome, the current study synthesizes the literatures on human capital and identity theory (Callero, 1985; Stryker, 1980; Turner, 1978); and theorize that experiences gained from career interventions may have a distal impact on IT career persistence.

The underlying thesis is that career interventions provide occupation-specific skills needed to carve a salient professional identity in IT. A salient professional identity will trigger attachment behaviors to the profession including the continuous pursuit of IT careers. Accordingly, this study complements extant turnaway research that offers little theoretical guidance on why some IT graduates persist in early IT careers and others do not.

Three, this research makes an empirical contribution to the broader career interventions literature. I rely on recent advances in analytical techniques to control and adjust for possible endogeneity that may bias the effect of college-based career interventions on initial IT employment. As such, the results of the current study are robust.

Career Interventions

While acknowledging that organizations also institute career interventions for employees (Hunt & Michael, 1983; Scandura, 1992), for the purposes of the current study I limit the scope of the review to career interventions in academic settings. Career interventions are school-to-work initiatives that immerse participants in a work-setting to learn about the real world of work (Narayanan et al., 2010).

Career interventions integrate formal academic training with work experience. Participants learn about the self in developing career pathways and improving future performance in a focal occupation. Career interventions may be supervised by faculty or a seasoned employee from the organization (Narayanan et al., 2010). In some cases, students are offered remunerations for participating in career interventions (Luecking & Fabian, 2000).

Three actors – students, colleges and organizations are involved in school-based career interventions, but student-centric outcomes of career interventions are perhaps the most examined. Specifically, the effect of internship experience on employment outcomes of students has been largely explored (see Table 1). The consensus is that internships prompt desirable employment outcomes (Callanan & Benzing, 2004; Fuller & Schoenberger, 1991).

Table 1: Summary Review

Study	Theory/Theoretical Perspective	Methodology	Career Intervention Examined	Sample	Major Findings
Aasheim et al. (2009) *	NA	Descriptive - Survey	Internship	IT managers, IT faculty	1. IT internship is cited in the top 3 most common sources of finding entry-level IT professionals.
Callanan and Benzing (2004)	NA	Quantitative – Logistic regression	Cooperative education, Internship	Business undergraduates	1. Internship experience is associated with finding career employment.
Colley and Jamison (1998)	NA	Descriptive - Survey	Integrated special education services	Former special education students	1. A higher percentage of respondents who participated in occupational education and received special education were in paid competitive employment compared with respondents who did not receive occupational education and special education services.
Dillon and Lending (2014) *	NA	Case study	IT consulting and mentorship programs	Computer and information systems graduates	1. Participants reported that the mentorship program provided real world insights about IT work and assisted in skills building.
Fuller and Schoenberger (1991)	NA	Quantitative -Ordinary least squares (OLS) regression	Internship	Business graduates	1. Internship experience is related to increased salaries.
Gault et al. (2000)	Learning and skills development	Quantitative – Multivariate analysis F test	Internship	Business graduates	1. The starting and current salaries of respondents who have internship experience is higher than respondents who have no internship experience.
Henry (Henry, 1979)	NA	Descriptive - Survey	Internship	Graduates	2. Internships reduced the time to find initial employment. 1. Respondents who have internship experience reported finding jobs quicker than respondents who have no internship experience.
Knouse, Tanner and Harris (1999)	Learning and skills development	Descriptive - Survey	Internship	Business graduates	2. A higher percentage of students who had internship experience found jobs compared to students who did not have internship experience.
Luecking and Fabian (2000)	NA	Quantitative - Logistic regression	Internship	Special education high school students	1. Completion of internships increased job offers from host organizations. 2. Completion of internships increased the likelihood of employment by 4 times.
Richards (Richards, 1984)	NA	Quantitative - Correlations	Internship	Liberal arts graduates	1. Internship experience is linked with higher levels of job stability.
Sagen et al. (2000)	Human Capital	Quantitative - Logistic regression	Cooperative education, Internship, Mentorship	Baccalaureate graduates	1. Cooperative education and internship experiences increase the likelihood of initial employment success. 2. Specialized-hard and soft (STEM) graduates increased their chances of initial employment compared with non-STEM graduates.

*IT Studies; NA = Not Applicable

Internships facilitate the learning of career relevant skills that cannot be readily transferred in the academic setting. Students concretize academic concepts, which are abstract, and apply them in the context of real work. The learning of job-relevant skills while in school supplements the general development of cognitive capacities and academic skills (Sagen et al., 2000).

Luecking and Fabian (2000) demonstrated that students who completed the “Bridges Internship Program” developed by the Marriott Foundation for people with disability were four times more likely to be employed 6 months after the internship. Of the 2119 students who completed the internship program, 68% found employment within 6 months after completing the internship. The 6-month post internship employment rate is consistent with the findings from other studies (Colley & Jamison, 1998). Luecking and Fabian (2000) attribute their findings to the productivity-enhancing nature of internships and the value employers place on job experience.

The relationship between career interventions and employment outcomes is nuanced. STEM participants are more likely to secure initial employment relative to non-STEM participants (Sagen et al., 2000). In addition, career interventions are associated with objective early career success (Gault, Redington, & Schlager, 2000). Prior research has shown that students who participants receive higher entry-level salaries after graduation (Fuller & Schoenberger, 1991; Gault et al., 2000). In sum, the literature provides some evidence that suggests that career interventions play an important role in assisting individuals find employment, especially in their initial jobs.

High Direct and Low Direct Experiences of Career Interventions

College-based career interventions prepare IT graduates for a future career in IT in terms of acquiring task-specific skills. The literature on experiential and social learning theory guides our thinking of how task-specific skills are conveyed (Bandura & Walters, 1977; Kolb, 2014; Watts, 1996). Individuals acquire task-specific skills through hands-on or direct experience (Kolb, 2014; Watts, 1996). Individuals may also acquire task-specific skills via observational learning and social interaction (Bandura & Walters, 1977).

Guided by the arguments flowing from the experiential and social learning literature, I argue that participants enrolled in a career intervention program may acquire task-specific skills by (1) directly performing work and (2) observing seasoned professionals perform work. Often, the two methods of skills acquisition are not exclusive to a specific modality of career intervention, but coexist. However, the degree of task-specific skills gained from a specific modality of career intervention may vary.

A review of the literature suggests that internship (Callanan & Benzing, 2004; Ducat, 1980; Henry, 1979), mentorship (Linnehan, 2001; Pan, Sun, & Chow, 2011) and cooperative education (Ducat, 1980) require participants to assume occupational roles and directly perform work-related tasks and functions over a sustained period. The degree of task-specific skills gained from these interventions are relatively high, resulting in a high direct experience of career intervention.

In contrast, other career interventions including job shadowing are less sustained (Rogers, 1996; Turner & Lapan, 2002). Job shadowing offers participants the opportunity to visit an occupational setting of interest and observe seasoned professionals perform their daily work tasks (Rogers, 1996; Turner & Lapan, 2002). The degree of task-specific skills gained from job shadowing is comparatively low because participants do not directly perform tasks, resulting in low direct experience of career intervention.

As depicted in Figure 1, I content that the degree of task-specific skills gained from different modalities of career intervention lie on a continuum of low and high direct experiences. Low direct experience of career interventions conveys a relatively lower degree of task-specific skills, whereas high direct experience of career interventions conveys more task-specific skills.

Figure 1: High – Low Direct Experiences of Career Interventions

Theory and Hypotheses Development

Career Interventions and Initial IT Employment

Human capital theory (Becker, 1975) is relevant in delineating why employment outcomes are related to the experience gained from career interventions. Human capital theory (Becker, 1975) posits that investments in occupation-specific human capital raise individual worker productivity, which prompts better employment outcomes (Becker, 1975; Mincer, 1970).

Occupation-specific human capital refers to education and work experience attributes confined to a specific occupational domain. Investment in occupation-specific human capital entails the building of knowledge and task-specific skills that are productively utilized by prospective employers. Figure 2 presents the theoretical model.

Figure 2: High and Low Direct Experiences and Initial IT Employment

High Direct Experience and Initial IT Employment

Via the lens of human capital theory and in the context of the IT profession, high direct experience represents investments in task-specific skills or IT-specific human capital. IT-specific human capital amassed from IT work are sine qua non for solving problems and completing tasks including computer

programming, analysis and design of computer systems and networks (Huckman, Staats, & Upton, 2009). IT-specific human capital raises the ability of individuals to perform tasks (Littlepage, Robison, & Reddington, 1997). Thus, high direct experience gained from career interventions raises task performance and future productivity in IT work.

Much of the organizational success and profitability that employers pursue relies on the productivity of their workforce (Bapna, Langer, Mehra, Gopal, & Gupta, 2013). As such, employers value individual worker productivity. They are likely to offer jobs to prospective workers who are endowed with productive human capital including high direct experience of career interventions.

Prior research has demonstrated that students who complete internships receive a significantly higher number of job offers (Luecking & Fabian, 2000). Consistent with this finding and the theoretical arguments, I expect high direct experience of college-based career interventions to raise the employability of IT graduates as they transition into the IT labor market. Accordingly,

Hypothesis 1: *High direct experience of college-based career interventions increases the likelihood of initial IT employment.*

Low Direct Experience and Initial IT Employment

Low direct experience of career interventions entails that participants interact with and observe seasoned professionals perform work. Participants are able to form mental models of how resources must be combined and sequenced to replicate a task, routine or work behavior that achieves a desired work

outcome (Bandura & Walters, 1977). They learn and assimilate into the norms, values and culture of the occupation (Hunt & Michael, 1983; Tesluk & Jacobs, 1998). Assimilating into the norms, values and culture of an occupation translates to the adoption of in-role professional behaviors that have productivity implications on work (Guzman, Joseph, Papamichail, & Stanton, 2007; Ramachandran & Rao, 2006).

In this view, low direct experience of career interventions enable IT graduates to form pragmatic mental models of how to execute work roles. Further, shared interactions with seasoned IT professionals set the expectation of the norms, values and culture of the IT profession. The interactions also inform IT graduates about the outcome expectancies of adhering to the norms and values of the IT occupational culture (Stanton, Guzman, & Fagnot, 2006).

Building mental models of how to correctly execute work tasks and assimilating into the IT occupational culture contribute to the development of IT graduates' stock of human capital, which proves valuable to prospective employers (Becker, 1975; Ramachandran & Rao, 2006; Tesluk & Jacobs, 1998). Human capital theory suggests that learning experiences that have the potential of improving one's stock of human capital results in better employment outcomes (Becker, 1975; Smith, 2010). Accordingly, I hypothesize that

Hypothesis 2: *Low direct experience of college-based career interventions increases the likelihood of initial IT employment.*

Career Interventions and IT Career Persistence

Career persistence refers to the continuous pursuit of a profession as a career (Donohue, 2006). It reflects an individual's level of commitment to the profession (Donohue, 2006; Srinivasan, Murty, & Nakra, 2013), manifested as an adherence to the norms and values of the profession. Adherence to a social group's norms and values is reinforced when the individual is well socialized into the group or strongly identifies with the group (Frese, 1982; Moore, 1969). By corollary, I argue that persistence in a career is facilitated by the formation of a strong professional identity.

In this section I integrate concepts from the human capital literature and identity theory (Frese, 1982; Moore, 1969) to develop a set of hypotheses relating high and low direct experiences of career interventions to IT career persistence. Figure 3 presents the theoretical model.

Figure 3: High and Low Direct Experiences and IT Career Persistence

High Direct Experience and IT Career Persistence

High direct experience gained from college-based career interventions develops IT-specific human capital (Trauth et al., 1993). The development of occupation-specific human capital strengthens an individual's occupational

orientation (Pratt, Rockmann, & Kaufmann, 2006). IT graduates begin to identify strongly with the IT occupation than they initially did. A reinforced identity is elevated within the hierarchy of multiple identities that an individual may hold (Callero, 1985).

The elevated occupational identity becomes salient (Callero, 1985; Stryker, 1980). To reaffirm the salient occupational identity the individual engages in behaviors that are consistent with the norms and values of the profession (Callero, 1985; Stryker, 1980). The most proximal of such behaviors would be to remain in the IT profession and persist in IT careers.

Prior research has demonstrated that IT professionals who identify strongly with the profession report lower intentions of leaving the profession (Brooks, Hardgrave, O’Leary-Kelly, McKinney, & Wilson, 2015). In view of this evidence and the arguments, I expect high direct experience gained from college-based career interventions to prompt persistence in IT careers.

Hypothesis 3: *The relationship between high direct experience of college-based career intervention and IT career persistence is positive.*

Low Direct Experience and IT Career Persistence

By observing and interacting with seasoned IT professionals, IT graduates learn about the occupational culture (Ramachandran & Rao, 2006; Trice, 1993). IT graduates’ understanding of the occupational culture becomes salient, which enables them to internalize the norms and values required for professional practice. The internalization of occupational norms, and values reinforces a sense of belonging to the IT profession (Duliba & Baroudi, 1991;

Frese, 1982; Orlikowski & Baroudi, 1988). Low direct experience gained from college-based career interventions therefore strengthens the sense of membership to the profession or professional identity.

According to identity theory (Callero, 1985; Stryker, 1980; Turner, 1978), a strengthened professional identity would elicit behaviors that reaffirm and validate one's association with the profession. The most proximal of such behaviors will be to remain in the IT profession. Accordingly, I hypothesize

Hypothesis 4: *The relationship between low direct experience gained from college-based career intervention and IT career persistence is positive.*

Methodology

This section begins with a detailed description of the dataset and the criteria used for constructing the samples. I provide a description of the variables, operationalization of the variables and estimation techniques employed in testing the hypotheses.

Data

The samples are drawn from the National Longitudinal Survey for Youth 1997 (NLSY97) cohort dataset (US Bureau of Labor Statistics, 2016). The NLSY97 dataset is particularly suited for the present analysis for the following reasons. The NLSY97 documents young adult life transitions including youth entry into the labor force. Furthermore, the NLSY97 cohort is a national representative sample. A representative sample reduces threats to external validity and increases the generalizability of the results (Cook, Campbell, & Day, 1979).

The sampling design comprises of two phases (Moore, Pedlow, Krishnamurty, Wolter, & Chicago, 2000; US Bureau of Labor Statistics, 2016). For the first phase, a list of 96512 housing units or households were selected via probabilistic sampling to ensure an accurate representation of the US population defined by socioeconomic status, ethnicity, region of residence and other socio-demographic variables. In the second phase, subsamples of eligible persons identified from the list of housing units were selected for interview. The NLSY97-eligible persons were individuals born between 1980 and 1984 (age 12-16 as of December 31, 1996).

The NLSY97 Survey

Sponsored and funded by the Department of Labor (DOL), the NLSY97 survey examines the lives of a sample of youthful Americans within the age range of 12 and 16 years as of December 31, 1996. The survey is administered by researchers from the National Opinion Research Center (NORC) under the auspices of the US Bureau of Labor Statistics. The researchers interview, administer questionnaires and collect information about respondents in a longitudinal fashion.

The first round of the survey was administered in 1997 and followed a sample of 8984 youthful Americans (Moore, Pedlow, Krishnamurty, Wolter, & Chicago, 2000). The NLSY97 remains an active survey project which mostly runs annually. The most recent round of the NLSY97 data, available to the public, is the 15th round. The 15th survey round was conducted in 2012. Cumulative attrition has reduced the sample to 7141 respondents as of 2012.

The NLSY97 collects extensive information on a broad range of topics such as educational experiences, demography, employment and labor market activities. Employment data consists of variables including, but not limited to, a respondent's job start and stop dates, occupations, working hours, wages, job search activities, firm tenure and job mobility.

Educational data captures information about respondents' schooling history including dates of college enrollment and graduation, fields of study, enrollment into career interventions, academic performance and degrees attained. Demographical and biographical data include birth dates, ethnicity,

place of residence in the United States and annual household income. The NLSY97 also collects information on the general health status of respondents in all the rounds.

College-Based Career Interventions and Initial IT Employment

Sample Construction

To estimate the influence of college-based career interventions on initial IT employment, a sample for the analysis is constructed from the universe of 8984 NLSY97 respondents. Respondents qualify to be included in the study sample when they meet the following criteria.

One, respondents must have attained an associate's or bachelor's degree in an IT field of study and provided the date of graduation. A respondent's field of study in the NLSY97 dataset is identified by the Classification Instructional Program (CIP) codes developed by the US National Center for Education Statistics (NCES). An IT degree includes the following: computer and information sciences, information technology, computer programming, computer information systems, computer systems analysis, computer/software engineering and business/management information systems and data processing.

Two, respondents must have actively searched for a job after completing college. For all survey rounds, the NLSY97 asks respondents to report if they have actively searched for a job via one or more of the following methods: contacting employers directly, contacting employment agencies and sending out resumes or filling out job applications (US Bureau of Labor Statistics, 2015b).

These job search methods are denoted as active job searching because they may result in the offer of a job without any further action on the part of the job seeker (US Bureau of Labor Statistics, 2015b)

Finally, respondents must have no record of IT employment before enrolling into college. This is to rule out the possibility that prior working experience in IT may influence employment at graduation. The NLSY97 provides both part-time and full-time employment information of respondents.

A total of 318 respondents met the three criteria. The final sample of 318 individuals consists of 219 (68.9%) males and 99 (31.1%) females. In regards to ethnicity, 58.8% are of white ethnicity, 23.6% are African-Americans and the remaining 17.6% are Hispanics and Mixed race. In terms of education credentials, 66.4% have attained a bachelor's degree and 33.6% have attained an associate's degree; 62.0% have attained degrees from public colleges and 38.0% have attained degrees from private colleges.

Data Analytical Approach

A survival analysis technique is used for the analysis. The dependent variable in survival analysis technique is composed of two parts i.e. the occurrence of the event and the event time, which is the elapsed time to the event (Allison, 2010). An event is defined as a qualitative change in state that involves a transition from one stage to another (Allison, 2010). The technique estimates two functions– the *survival* and *hazard* functions that describe the distribution of the event time.

The survival function $S(t_i)$ is the probability that, for every unit time t within the period of observation, an individual i survives (or does not experience) the event of interest up to that time t . The hazard function $\lambda(t_i)$ is the likelihood that the event will occur on condition that the individual has survived the event up to the specified time t .

Survival analysis uses the Maximum Likelihood function (L) to estimate the parameters of the survival and hazard functions. The L function is the product of the survival and hazard functions. Thus, if an individual i experiences the event of interest at time t_i his or her contribution to the likelihood function is expressed as $L_i = S(t_i)\lambda(t_i)$.

A key strength of survival analysis over standard applications of ordinary least square (OLS) regressions is the capability to circumvent the limitations of censored observations (Allison, 1984). Censoring occurs when an individual either exits the study before the end of the observation period or does not experience the event before the end of the observation period. Failure to analytically incorporate censoring information in the estimation process could bias the results and threaten the interval validity of the study (Allison, 1984; Cook et al., 1979).

Survival analysis carefully incorporates censoring information in the estimation process as follows. Recall that the hazard function $\lambda(t_i)$ is the likelihood that the event has occurred given that the individual has survived up to the time t . In cases of censoring, the event never occurs. Therefore, there is

no hazard function $\lambda(t_i)$ for a censored observation. Thus, the contribution of a censored observation to the Likelihood function is $L_i = S(t_i)$ instead of $L_i = S(t_i)\lambda(t_i)$. By accounting for censoring in the estimation process, survival analysis technique produces unbiased estimates (Allison, 1984).

In the case of the current study, the event of interest is initial IT employment. Participants experience the event when they transition from college into IT jobs before the end of the observation period. For the current study the end of the observation period coincides with the last round of the NLSY97 survey, which was conducted in 2012. The NLSY97 identifies jobs using the 2002 Standard Occupational Classification SOC codes (US Bureau of Labor Statistics, 2014). Table 2 presents the list of IT jobs identified by the NLSY97.

Table 2: NLSY97 Job Titles

OCS 2002 Code	Job Title
1000	Computer Systems Analyst
1010	Computer Programmer
1020	Computer Software Engineer
1040	Computer Support Specialist
1060	Database Administrator
1100	Network and Computer Systems Administrator
1110	Network Systems and Data Communication Analyst
1400	Computer Hardware Engineer

Observations are censored when one of the following occurs: (1) participants transition into non-IT job roles or (2) participants do not enter the labor market before the end of the observation period. Figure 4 provides an

example of the data structure and how the current study treats college graduation to IT employment transition and censoring.

Figure 4: College Graduation-IT Employment Transition and Censoring

In testing hypotheses 1 and 2, a parametric survival analysis model is used. Parametric survival models incorporate full information from the data in the estimation process (Allison, 1984, 2010). The models are efficient to estimate because the distributions of the survival times – *the unemployment period between college graduation and initial IT employment* – are known.

Specifically, the current study uses the Weibull parametric survival hazard model for the analysis. The Weibull parametric model has a monotonic hazard function, suggesting that the hazard or risk of experiencing the event is either always increasing with time or decreasing with time but never changes direction (Allison, 1984, 2010). This property of the hazard function accords well with Heckman and Singer’s (1982) thesis that the hazard or risk of securing employment always increases with the period of job search. Essentially, the

likelihood that an individual finds a job increases so far as the individual continues to search for the job.

To further validate Heckman and Singer's thesis, I graphed a diagnostic plot of the survival times of the current study's observations. The plot revealed that the distribution of the survival times follow a Weibull distribution (see Appendix I, Figure 8).

The Weibull parametric model is given by equation 1. Equation 1 models the logarithmic value of the hazard function $\lambda(t)$ conditional on n number of covariates X or explanatory variables. Intuitively, the hazard function $\lambda(t)$ models the hazard or risk (i.e. the probability of securing initial IT employment) at time t that an individual who is yet to experience the event of interest faces (Allison, 2010).

$$\log \lambda(t) = c \log t + \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_n X_n \quad \text{Equation [1]}$$

Where t is the survival time, c is a constant and β_n represents the regression coefficients.

To ease interpretation, the unstandardized regression coefficients of a Weibull parametric model are transformed as Hazard Ratios (HR). The hazard ratio is the relative hazard of experiencing an event at two levels (high and low) of a covariate, when all other covariates are constant. For a categorical variable with values of 1 and 0, the hazard ratio should be interpreted as the ratio of the estimated hazard for those with a value of 1 to the estimated hazard for those with a value of 0, when all other covariates are held at a constant. Equation 2

presents the Hazard Ratio for a given covariate X at time t for a specified Weibull parametric model.

$$HR = \frac{\log \lambda(t|X_1, X_i+1, \dots, X_p)}{\log \lambda(t|X_1, X_i, \dots, X_p)} \quad \text{Equation [2]}$$

Measures

Dependent Variable: The dependent variable is the hazard to initial IT employment, $\log \lambda(t)$. The hazard to initial IT employment is the likelihood that an individual finds IT employment at graduation.

Explanatory Variables: The explanatory variables are *high direct* and *high indirect* experiences gained from college-based career interventions. The NLSY97 asks respondents if they participated in a work-based learning program at school (NLSY97, 2016). I consider work-based learning programs at the college level. These are cooperative education, internship, mentorship and job shadowing.

High Direct Experience. *Cooperative Education* (CoopExp), *Internship* (InternExp) and *Mentorship* (MentorExp) experiences are high direct experiences of career interventions. Table 3 provides the NLSY97 definitions of the career interventions. Cooperative education experience is measured with a dichotomous variable; “1” if a respondent enrolled in cooperative education and “0” if respondent did not enroll in the program. Internship experience is a dichotomous variable; “1” if a respondent participated in an internship and “0” if respondent did not participate in the program. Mentorship experience is

measured with a dichotomous variable; “1” if a respondent participated in a mentorship program and “0” if a respondent did not participate in the program.

Table 3: NLSY Definitions of Career Interventions

Intervention	Definition
Cooperative education	Students alternate or parallel their academic and vocational studies with a job in a related field.
Internship	Students work for an employer for a short time to learn about a particular industry or occupation.
Mentorship	A student is paired with an employee who assesses his or her performance over a period of time, during which the employee helps the student master certain skills and knowledge.
Job Shadowing	A student follows an employee for one or more days to learn about an occupation or industry.

Source: NLSY97 (2016)

Low Direct Experience. *Job Shadowing* (JobShadExp) experience is low direct experience of career interventions. Job shadowing experience is measured with a dichotomous variable; “1” if a respondent participated in a job shadowing program and “0” if a respondent did not participate in the program.

Control Variables: Guided by prior research, I included a series of control variables in the model. To account for the possible influence of individual aptitude on the hazard of initial IT employment, I controlled for *Cognitive Ability* and *Academic Performance* (Brown, Hesketh, & Williams, 2004; Pinto & Ramalheira, 2017). Cognitive ability (CogAbility) is a measure of the Armed Services Vocational Aptitude Battery (ASVAB) scores. The NLSY97 administered a computer-adaptive version of the ASVAB test to respondents in the first round of the survey. The ASVAB measures a respondent’s aptitude in the following areas: arithmetic reasoning, assembling

objects, auto information, coding speed, electronics information, general science, mathematics knowledge, mechanical comprehension, numerical operations, paragraph comprehension, shop information and word knowledge.

The ASVAB test design is founded on Items Response Theory (IRT). IRT enables the NLSY97 to place the test questions and the respondent's abilities on the same scale. The test is thus tailored to the specific ability level of each respondent regardless of age differences.

Academic performance (AcadPerf) is a standardized measure of the final Grade Point Average (GPA). GPA is measured on a 4-point scale. Academic performance and cognitive ability variables are logged for easier interpretation. *Education level* (EduLevel) is a dichotomous variable coded as "1" if respondent attained a bachelor's degree and "0" if respondent attained an associate's degree. *College Type* (ColType) is coded as "1" if respondents graduated from a public college and "0" if respondents graduated from a private college.

Ethnicity is a categorical variable ("1" = White, "2" = African-American and "0" = Other). *Sex* is coded as "1" = Male and "0" = Female. *Socioeconomic Status* (SES) is a logged measure of the annual household income (USD) of a respondent. Household income is adjusted for inflation using the consumer price index (CPI) deflator with 2016 as the base year.

Guided by the job search literature, I accounted for the potential effect of median wage rate of a job on the likelihood of initial IT employment. The theory of optimal stopping as applied in the job search literature posits that the

period of job search or unemployment period is contingent on the wage rate individuals believe is commensurate with their human capital endowment (McCall, 1970; Mortensen, 1970). A candidate would reject job offers, which do not maximize expected earnings, and remain unemployed (McCall, 1970).

Median Wage Rate (MedianWageRate) is a measure of the industry median hourly rate of pay (USD) for a focal IT job. Median wage rate is adjusted for inflation using the CPI deflator with 2016 as the base year. The BLS provides estimates of the weekly and hourly median rate of pay of jobs. The estimates are calculated with data collected from employers in all the occupations identified by the SOC codes.

To account for the year-on-year employment situation in the US, the official unemployment rate for the corresponding year that a respondent graduated college was included in the model. *Yearly Unemployment Rate* (YUR) is the ratio of the number of unemployed persons who are actively looking for a job to the total number of employed and unemployed people in each year expressed as a percentage (US Bureau of Labor Statistics, 2015). I also controlled for the geographic location of a respondent in the United States. *Region* is a four-level categorical variable (“1” = North Central; “2” = South; “3” = West and “0” = South). Further, urban and rural residents are coded (“1” = Urban; “0” = Rural). All categorical variables coded as “0” are reference categories.

I controlled for the duration of the intervention program. *Duration of College-Based Career Intervention* (DurationCBCI) is a measure of the total

number of months an individual participated in one or more of a college-based career intervention. I decided against controlling for the effect of career intervention remuneration. This decision is informed by the presence of multicollinearity. Cooperative education experience is perfectly correlated with the dummy variable that captures whether respondents received pay for participating in any of the college-based career interventions.

Empirical Model

Equation 3 presents the empirical model. The hazard risk to initial IT employment λ at a time t is expressed as a function of the substantive explanatory and control variables.

$$\begin{aligned} \log \lambda(t) = & \beta_0 + \beta_1 YUR + \beta_{2-4} Region + \beta_5 Urban + \beta_6 Sex + \\ & \beta_{7-8} Ethnicity + \beta_9 SES + \beta_{10} CollegeType + \beta_{11} EduLevel + \\ & \beta_{12} AcadPerf + \beta_{13} CogAbility + \beta_{14} MedianWageRate + \\ & \beta_{15} DurationCBCI + \beta_{16} CoopExp + \beta_{17} InternExp + \\ & \beta_{18} MentorExp + \beta_{19} JobShadExp \end{aligned} \quad \text{Equation [3]}$$

Career Interventions and IT Career Persistence

Measures

Table 4 presents a description and definition of the study variables.

Dependent Variable: The dependent variable is *IT Career Persistence* (CP). IT career persistence is defined as the continuous pursuit of IT as a profession. IT career persistence is operationalized as the cumulative number of years an individual has spent in IT job roles.

Explanatory Variables: The explanatory variables are *high direct* and *low direct* experiences of career interventions. *Cooperative Education*, *Internship* and *Mentorship* experiences are high direct experiences of career interventions. *Job Shadowing* experience is low direct experience of career interventions. Cooperative education, internship, mentorship and job shadowing experiences are dichotomous variables coded as “1” if a respondent participated in a focal program and “0” if a respondent did not participate in the program while in college.

Control Variables: I included a series of variables to rule out alternate explanations for IT career persistence. I controlled for *Cognitive Ability* and *Academic Performance*. The rationale for including cognitive ability and academic performance as control variables stems from the idea that the IT profession is a knowledge-intensive discipline. IT professionals who have demonstrable knowledge and aptitude may thrive more and show greater persistence in IT careers. Cognitive ability is the logged measure of the ASVAB test scores. Academic performance is a measure of the final GPA.

In addition, I controlled for *Education Level* (“1” = Bachelor’s degree; “0” = Associate’s degree) and *College Type* (“1” = Public College; “0” = Private College). Prior research has demonstrated that social minorities in the US including African-Americans and females are less persistent in STEM careers (Blickenstaff, 2005; Cech, Rubineau, Silbey, & Seron, 2011). Accordingly, I controlled for *Sex* and *Ethnicity*. Sex is coded as “1” = Male; “0” = Female.

Ethnicity is coded as “1” = White; “2” = African-American; “0” = Hispanics and Mixed Race.

Holland’s (1997) study on personality-job congruence opine that individuals tend to remain in careers that conform with their personality orientation. Further evidence from personality research in IT suggests that traits of extraversion and emotional resilience are associated with increased levels of career commitment, which describes one’s level of motivation to remain or persist in a choose field of occupation (Blau, 1985; Lounsbury et al., 2009). In view of this, I controlled for traits of *Extraversion* and *Emotional Resilience*. The NLSY97 collects information on personality traits. Respondents rate how well extraversion and emotional resilience personality traits are applicable to them on a 7-point Likert scale (“1” = Disagree strongly ... “7” = Agree strongly).

IT jobs are stressful (Sethi, King, & Quick, 2004). It is conceivable to argue that in the face of chronic stress caused by job-specific stressors (e.g. long working hours) IT professionals may withdraw from IT careers (Shropshire & Kadlec, 2012). Accordingly, I controlled for occupational stress with *Working Hours*.

Table 4: Variable Definition

Study	Variable	Definition
Dependent Variables		
I	Hazard Risk to Initial IT Employment Success	Likelihood of finding initial IT employment at graduation.
II	IT Career Persistence	Continuous pursuit of IT careers operationalized as the cumulative number of years spent in the IT profession.
Control Variables		
I	Yearly Unemployment Rate	Ratio of the number of unemployed persons to the total number of employed and unemployed persons in the US in a year.
I, II	Region: North Central; South; West	Geographic region of residence in the US with the Northeast as the reference category.
I	Urban	Respondent's residence is within an urban area; rural is the reference category.
I, II	Sex: Male	Biological classification of respondent as male; female is the reference category.
I, II	Ethnicity: White; African- American	Respondent's ethnic affiliation; Hispanic is the reference category.
I	Socioeconomic Status	Real annual household income of respondent.
I, II	College Type: Public College	College attended is publicly funded; reference category is private college.
I, II	Education Level: Bachelor's Degree	Level of education attained; reference category is Associate's Degree.
I, II	Academic Performance	Measure of Grade Point Average (GPA).
I, II	Cognitive Ability	Measure of level of general ability.
II	Job Type: Computer Support & Systems Analyst; Computer Programmer and Developer	Standard Occupational Classification code of respondent's job; reference category is Other jobs.
I	Median Wage Rate	Median hourly rate of pay for a focal job identified by SOC code.
II	Wage Rate	Real hourly rate of pay.
II	Working Hours	Weekly working hours.
II	Industry Type: Professional, Business or Finance; Retail & Trade; Manufacturing	Standard Industry Classification code of respondent's job; reference category is Other jobs.
I	Duration of College-Based Career Intervention	Total number of months a respondent participated in one or more of the college-based career intervention programs.
II	Job Satisfaction	Affective attachment to a job.
II	Extraversion	Respondent's tendency to be sociable.
II	Emotional Resilience	Respondent's tendency to adapt to difficult situations.
Explanatory Variables		
High Direct Experiences		
I, II	Cooperative Education Experience	Respondent alternates academic studies with full-time paid work.
I, II	Internship Experience	Respondent works with an employer in a short time.
I, II	Mentorship Experience	Respondent is paired with a seasoned employee who helps the respondent to master certain skills and knowledge.
Low Direct Experience		
I, II	Job Shadowing Experience	Respondent shadows a seasoned employee at the workplace.

Study I refers to the study on Career Interventions and Initial IT Employment; Study II refers to the study on Career Interventions and IT Career Persistence.

Working hours is a lagged (t-1) measure of the number of weekly working hours. *Industry Type* is a lagged categorical variable (Professional, Business or Finance; “2” = Retail and Trade industry; “3” = Manufacturing and “0” = Other industries). Lagging variables increases the predictive power of the variables. It also reduces the possibility of simultaneity bias between independent and dependent variables (Singer & Willett, 1991).

Prior research (Joseph et al., 2015) has found that job satisfaction levels influence voluntary exit of IT professionals into non-IT jobs. Accordingly, I controlled for lagged measures *Job Satisfaction*. The NLSY97 asks respondents to rate how they feel about their current job on a (reverse coded) 5-point Likert scale (“1” = Dislike it very much ... “5” = Like it very much). I controlled for lagged measures of *Wage Rate*. Wage rate is a measure of the hourly rate of pay adjusted for inflation using the CPI deflator with 2016 as the base year.

Data Analysis

The dependent variable IT Career Persistence, CP, is either zero or a positive number. For the current study, CP equals zero if a respondent never enters an IT job role after graduating. The CP variable is therefore left-censored at zero; and thus, the CP variable has a censored distribution.

For censored distributions of dependent variables, standard linear panel regressions including generalized linear model (GLM) would produce inconsistent estimates and hence, are inappropriate for the current analysis (Greene, 2000; Wooldridge, 2010). For the current analysis, I use a random

effects Tobit panel regression (with censoring at zero) to estimate the predictors of IT career persistence.

A Tobit regression is appropriate when the “dependent variable has a number of its values clustered at a limiting value, usually zero” (McDonald & Moffitt, 1980, p. 318). The regression accounts for censored distribution by combining the Probit likelihood of observing censored observation with the linear regression likelihood to explain uncensored observation, thereby resulting in consistent estimates (Greene, 2000).

I estimate the empirical model by specifying the (uncensored) dependent variable CP_{it}^* as a function of the regressors, an idiosyncratic error ε_{it} and individual-specific error α_i . The empirical model is estimated at the person-period unit of analysis.

$$\begin{aligned}
 CP_{it}^* = & \beta_0 + \beta_1 WorkingHours_{i,t-1} + \beta_2 JobSatisfaction_{i,t-1} + \\
 & \beta_3 Wages_{i,t-1} + \beta_{4-6} IndustryType_{i,t-1} + \beta_7 AcademicPerformance_i + \\
 & \beta_8 CognitiveAbility_i + \beta_9 EduLevel_i + \beta_{10} CollegeType_i + \beta_{11} Sex_i + \\
 & \beta_{12-13} Ethnicity_i + \beta_{14} Extraversion_i + \beta_{15} EmotionalResilience_i + \\
 & \beta_{16} CoopExp_i + \beta_{17} InternExp_i + \beta_{18} MentorExp_i + \\
 & \beta_{19} JobShadowExp_i + \alpha_i + \varepsilon_{it}; \text{ where } \varepsilon_{it} \sim N(0, \sigma_\varepsilon^2) \text{ and } \alpha_i \sim N(0, \sigma_\alpha^2)
 \end{aligned}$$

$$CP_{it} = \begin{cases} CP_{it}^*, & \text{if } CP_{it}^* > 0 \\ 0, & \text{if } CP_{it}^* = 0 \end{cases} \quad \text{Equation [4]}$$

where i indexes individuals; $t-1$ indexes one year lag relative to t th year in the labor force.

Results

Career Interventions and Initial IT Employment

Table 5 presents the descriptive statistics and correlations of the variables. Table 6 shows the results of the Weibull parametric model. The estimates are the unstandardized regression coefficients from the Weibull parametric model. Model I of Table 6 presents the results of only the control variables. Model II of Table 6 presents the results of the full model.

Hypothesis 1 predicted that high direct experience gained from college-based career interventions increases the likelihood of initial IT employment. Results from Table 6 (Model II) indicate that the relationship between cooperative education experience and the hazard risk to initial IT employment is positive and significant ($\beta_{16} = 0.902, t = 2.550, p < 0.05$). The hazard ratio indicates that a unit increase in cooperative education experience increases the likelihood of initial IT employment by a factor of 2.5.

Results from Table 6 (Model II) indicate that the relationship between internship experience and the hazard risk to initial IT employment is positive and significant ($\beta_{17} = 0.418, t = 2.150, p < 0.05$). The hazard ratio indicates that internship experience increases the likelihood of initial IT employment by a factor of 1.5.

Results from Table 6 (Model II) indicate that the relationship between mentorship experience and the hazard risk to initial IT employment is positive and significant ($\beta_{18} = 0.610, t = 2.940, p < 0.01$). The hazard ratio indicates

that mentorship experience increases the likelihood of initial IT employment by a factor of 1.8. Hypothesis 1 is therefore supported.

Hypothesis 2 predicted that low direct experience gained from college-based career intervention increases the likelihood of initial IT employment. Results from Table 6 (Model II) indicate that the relationship between job shadowing experience and the hazard risk to IT employment is negative but not significantly different than zero ($\beta_{19} = -0.123, t = -0.290, n.s.$). Hypothesis 2 is not supported.

Table 5: Descriptive Statistics and Correlations

	Mean	SD	1	2	3	4	5	6
1 Survival Time (Unemployment period)	5.758	5.492						
2 Yearly Unemployment Rate	5.699	1.496	0.077					
3 Region: North Central	0.230	0.421	0.023	0.044				
4 Region: South	0.358	0.480	0.021	-0.009	-0.408**			
5 Region: West	2.579	1.035	0.074	-0.002	-0.306**	0.305**		
6 Urban	0.796	0.404	-0.605**	-0.083	0.036	-0.076	-0.154**	
7 Sex: Male	0.689	0.464	-0.119*	-0.060	0.092	-0.064	0.035	0.063
8 Ethnicity: White	0.588	0.493	-0.098	-0.008	0.244**	-0.240**	-0.075	0.114*
9 Ethnicity: African-American	0.236	0.425	-0.019	-0.029	-0.145**	0.388**	-0.017	-0.067
10 Socioeconomic Status	10.996	0.957	-0.124*	-0.065	0.019	-0.067	0.008	0.036
11 Public College	0.620	0.486	-0.018	0.052	0.012	0.046	0.113*	0.036
12 Bachelor's Degree	0.664	0.473	-0.112*	-0.104	-0.039	-0.078	-0.059	0.002
13 Academic Performance	3.207	0.536	-0.343**	-0.075	0.039	-0.077	-0.063	0.203**
14 Cognitive Ability	10.923	0.577	-0.018	-0.059	0.092	-0.151**	-0.048	0.092
15 Median Wage Rate	27.581	25.327	-0.192**	-0.026	-0.023	0.013	0.034	0.106
16 Duration of College-Based Career Intervention	2.179	2.441	-0.518**	-0.058	0.049	-0.066	-0.086	0.316**
17 Cooperative Education Experience	0.053	0.225	-0.153**	0.032	0.003	-0.032	-0.092	0.120*
18 Internship Experience	0.450	0.498	-0.463**	-0.158**	-0.058	-0.017	-0.023	0.380**
19 Mentorship Experience	0.387	0.488	-0.531**	-0.075	-0.080	0.053	-0.076	0.274**
20 Job Shadowing Experience	0.063	0.243	0.231**	0.002	-0.018	-0.032	0.106	-0.094

N = 318; SD = Standard Deviation; Survival Time denotes the time (in months) it takes an individual to enter the IT labor market.

Table 5: Descriptive Statistics and Correlations (continued)

	Mean	SD	7	8	9
1 Survival Time (Unemployment period)	5.758	5.492			
2 Yearly Unemployment Rate	5.699	1.496			
3 Region: North Central	0.230	0.421			
4 Region: South	0.358	0.480			
5 Region: West	2.579	1.035			
6 Urban	0.796	0.404			
7 Sex: Male	0.689	0.464			
8 Ethnicity: White	0.588	0.493	0.182**		
9 Ethnicity: African-American	0.236	0.425	-0.154**	-0.664**	
10 Socioeconomic Status	10.996	0.957	0.072	0.079	-0.114*
11 Public College	0.620	0.486	0.005	0.055	0.008
12 Bachelor's Degree	0.664	0.473	0.053	0.148**	-0.075
13 Academic Performance	3.207	0.536	0.012	0.111*	-0.089
14 Cognitive Ability	10.923	0.577	0.069	0.374**	-0.344**
15 Median Wage Rate	27.581	25.327	0.104	0.030	0.004
16 Duration of College-Based Career Intervention	2.179	2.441	0.016	0.046	0.011
17 Cooperative Education Experience	0.053	0.225	0.069	0.000	0.033
18 Internship Experience	0.450	0.498	0.034	-0.001	0.004
19 Mentorship Experience	0.387	0.488	-0.052	-0.017	0.106
20 Job Shadowing Experience	0.063	0.243	-0.050	-0.099	-0.022

N = 318; SD = Standard Deviation; Survival Time denotes the time (in months) it takes an individual to enter the IT labor market.

Table 5: Descriptive Statistics and Correlations (continued)

	Mean	SD	10	11	12	13	14
1 Survival Time (Unemployment period)	5.758	5.492					
2 Yearly Unemployment Rate	5.699	1.496					
3 Region: North Central	0.230	0.421					
4 Region: South	0.358	0.480					
5 Region: West	2.579	1.035					
6 Urban	0.796	0.404					
7 Sex: Male	0.689	0.464					
8 Ethnicity: White	0.588	0.493					
9 Ethnicity: African-American	0.236	0.425					
10 Socioeconomic Status	10.996	0.957					
11 Public College	0.620	0.486	-0.111*				
12 Bachelor's Degree	0.664	0.473	0.124*	-0.065			
13 Academic Performance	3.207	0.536	0.057	-0.127*	0.096		
14 Cognitive Ability	10.923	0.577	0.109	0.117*	0.277**	0.083	
15 Median Wage Rate	27.581	25.327	0.146**	0.049	0.171**	0.136*	0.112*
16 Duration of College-Based Career Intervention	2.179	2.441	0.080	-0.006	0.093	0.248**	-0.001
17 Cooperative Education Experience	0.053	0.225	0.081	-0.015	0.051	0.167**	0.020
18 Internship Experience	0.450	0.498	0.070	-0.008	0.135*	0.159**	0.052
19 Mentorship Experience	0.387	0.488	0.111*	-0.016	0.101	0.203**	0.028
20 Job Shadowing Experience	0.063	0.243	-0.059	0.043	-0.062	-0.093	-0.045

N = 318; SD = Standard Deviation; Survival Time denotes the time (in months) it takes an individual to enter the IT labor market.

* $p < 0.05$; ** $p < 0.01$.

Table 5: Descriptive Statistics and Correlations (continued)

	Mean	SD	15	16	17	18	19
1 Survival Time (Unemployment period)	5.758	5.492					
2 Yearly Unemployment Rate	5.699	1.496					
3 Region: North Central	0.230	0.421					
4 Region: South	0.358	0.480					
5 Region: West	2.579	1.035					
6 Urban	0.796	0.404					
7 Sex: Male	0.689	0.464					
8 Ethnicity: White	0.588	0.493					
9 Ethnicity: African-American	0.236	0.425					
10 Socioeconomic Status	10.996	0.957					
11 Public College	0.620	0.486					
12 Bachelor's Degree	0.664	0.473					
13 Academic Performance	3.207	0.536					
14 Cognitive Ability	10.923	0.577					
15 Median Wage Rate	27.581	25.327					
16 Duration of College-Based Career Intervention	2.179	2.441	0.165**				
17 Cooperative Education Experience	0.053	0.225	0.045	0.160**			
18 Internship Experience	0.450	0.498	0.089	0.403**	-0.038		
19 Mentorship Experience	0.387	0.488	0.204**	0.535**	-0.098	0.385**	
20 Job Shadowing Experience	0.063	0.243	-0.007	0.093	-0.004	-0.026	-0.046

N = 318; SD = Standard Deviation; Survival Time denotes the time (in months) it takes an individual to enter the IT labor market.

* $p < 0.05$; ** $p < 0.01$.

Table 6: Results of the Weibull Parametric Model Estimation

Dependent Variable: Hazard Risk to Initial IT Employment							
		Model I					
Control Variables		Estimate	se	t value	95% [CI]		HR
Intercept	β_0	-14.470***	2.086	-6.940	-18.558	-10.382	0.000
Yearly Unemployment Rate	β_1	-0.031	0.049	-0.630	-0.126	0.065	0.970
Region: North Central	β_2	-0.691***	0.198	-3.490	-1.079	-0.303	0.501
Region: South	β_3	-0.037	0.183	-0.200	-0.396	0.323	0.964
Region: West	β_4	-0.082	0.076	-1.080	-0.230	0.067	0.922
Urban	β_5	1.990***	0.312	6.390	1.380	2.601	7.318
Sex: Male	β_6	-0.385*	0.165	-2.330	-0.709	-0.061	0.681
Ethnicity: White	β_7	-0.096	0.199	-0.480	-0.486	0.294	0.908
Ethnicity: African-American	β_8	0.231	0.254	0.910	-0.268	0.730	1.260
Socioeconomic Status	β_9	0.115	0.079	1.450	-0.040	0.270	1.122
Public College	β_{10}	0.225	0.160	1.410	-0.089	0.538	1.252
Bachelor's Degree	β_{11}	0.319	0.173	1.840	-0.021	0.659	1.376
Academic Performance	β_{12}	0.102	0.154	0.660	-0.200	0.404	1.108
Cognitive Ability	β_{13}	0.031	0.148	0.210	-0.258	0.321	1.032
Median Wage Rate	β_{14}	0.002	0.002	0.870	-0.002	0.006	1.002
Duration of College-Based Career Intervention	β_{15}	0.173**	0.061	2.840	0.054	0.294	1.190
N				283			
Log Likelihood				-88.374			
df				16			
AIC				322.749			
Wald χ^2 (14)				256.850***			

* $p < 0.05$; ** $p < 0.01$ *** $p < 0.001$; se denotes the robust standard errors; CI denotes the confidence intervals of the estimates.
HR denotes the Hazard Ratio; df denotes the degrees of freedom.

Table 6: Results of the Weibull Parametric Model Estimation (continued)

Dependent Variable: Hazard Risk to Initial IT Employment							
Model II							
Control Variables		Estimate	se	t value	95% [CI]		HR
Intercept	β_0	-14.037***	2.188	-6.410	-18.326	-9.748	0.000
Yearly Unemployment Rate	β_1	-0.026	0.050	-0.510	-0.124	0.073	0.975
Region: North Central	β_2	-0.614**	0.201	-3.050	-1.009	-0.219	0.541
Region: South	β_3	-0.036	0.187	-0.190	-0.402	0.330	0.965
Region: West	β_4	-0.075	0.078	-0.960	-0.228	0.079	0.928
Urban	β_5	1.900***	0.322	5.910	1.270	2.531	6.688
Sex: Male	β_6	-0.380*	0.168	-2.270	-0.708	-0.051	0.684
Ethnicity: White	β_7	-0.168	0.208	-0.810	-0.575	0.239	0.845
Ethnicity: African-American	β_8	0.068	0.262	0.260	-0.445	0.582	1.071
Socioeconomic Status	β_9	0.088	0.082	1.080	-0.072	0.249	1.092
Public College	β_{10}	0.243	0.164	1.480	-0.078	0.564	1.275
Bachelor's Degree	β_{11}	0.274	0.178	1.540	-0.074	0.622	1.315
Academic Performance	β_{12}	0.098	0.152	0.650	-0.199	0.396	1.103
Cognitive Ability	β_{13}	-0.003	0.150	-0.020	-0.298	0.291	0.997
Median Wage Rate	β_{14}	0.002	0.002	0.880	-0.002	0.006	1.002
Duration of College-Based Career Intervention	β_{15}	0.174**	0.061	2.840	0.054	0.294	1.190
Explanatory Variables							
High Direct Experience H1							
Cooperative Education Experience	β_{16}	0.902*	0.354	2.550	0.207	1.596	2.464
Internship Experience	β_{17}	0.418*	0.194	2.150	0.037	0.798	1.518
Mentorship Experience	β_{18}	0.610**	0.207	2.940	0.204	1.017	1.841
Low Direct Experience H2							
Job Shadowing Experience	β_{19}	-0.123	0.425	-0.290	-0.956	0.709	0.884
N				283			
Log Likelihood				-201.439			
df				20			
AIC				442.878			
Wald χ^2 (18)				356.650***			

* $p < 0.05$; ** $p < 0.01$ *** $p < 0.001$; se denotes the robust standard errors; CI denotes the confidence intervals of the estimates. H1 and H2 denote hypotheses 1 and 2 respectively. HR denotes the Hazard Ratio; df denotes the degrees of freedom.

Endogeneity Concern

Unobserved heterogeneity could explain why an individual who participates in a college-based career intervention program may have a greater likelihood of initial IT employment. It is conceivable to argue that IT graduates who have a higher career-orientation would show greater interest in career intervention programs. They are more likely to participate in these programs when given the opportunity. Also, individuals with a higher career-orientation are more likely to succeed in the job market with regards to finding employment. In an econometric sense, college-based career intervention experiences are likely correlated with some omitted variables (unobserved individual heterogeneity) which also influence the likelihood of initial IT employment.

College-based career interventions are likely endogenous (Wooldridge, 2015). Insofar as college-based career interventions are endogenous, the parametric estimates of the Weibull parametric model would be inconsistent (Wooldridge, 2015). To alleviate concerns of endogeneity, I checked for the robustness of the estimates using a multilevel multiprocess estimation (MLMP) (Bartus, 2012; Lillard, 1993; Roodman, 2011). The MLMP analytical technique of adjusting for endogeneity is analogous to the instrumental variable (IV) estimation or two-stage least square (2SLS) estimation (Roodman, 2011; Wooldridge, 1997, 2015).

However, the MLMP estimator supports the estimation of survival models with endogenous regressors by incorporating information about

censored observations (Bartus, 2012). The 2SLS estimator is applied to standard applications of least square estimators which do not account for censored observations e.g. Ordinary Least Square (OLS). A detailed description of the MLMP estimation technique and the results are presented in Appendix II.

Overall, the results of the MLMP estimation are consistent with the initial results.

Career Intervention and IT Career Persistence

Table 7 presents the descriptive statistics and correlations for the study of college-based career intervention and IT career persistence. Table 8 presents the results of the Tobit panel regression analysis. The beta estimates are unstandardized regression coefficients and carry the same interpretation as the coefficients of ordinary least square (OLS) regressions. Models I and II of Table 8 present the results of only the control variables and the full model respectively.

Hypothesis 3 predicted a positive relationship between high direct experience of college-based career intervention and IT career persistence. Results from Table 8 (Model II) indicate that the relationship between cooperative education and IT career persistence is positive but not significant ($\beta_{16} = 0.531, t = 1.770, n.s.$). Results from Table 8 (Model II) indicate a positive and significant relationship between internship experience and IT career persistence ($\beta_{17} = 0.500, t = 3.220, p < 0.05$). Results from Table 8 (Model II) indicate a positive and significant relationship between mentorship experience and IT career persistence ($\beta_{18} = 0.845, t = 5.340, p < 0.001$). Hypothesis 3 is therefore partially supported.

Table 7: Descriptive Statistics and Correlations

	Mean	SD	1	2	3	4	5	6
1 IT Career Persistence	2.920	2.456						
2 Working Hours _{t-1}	40.920	0.021	0.021					
3 Job Satisfaction _{t-1}	3.080	0.910	-0.039	-0.058*				
4 Wage _{t-1}	26.131	92.491	-0.010	0.004	-0.057*			
5 Industry Type _{t-1} : Professional, Business or Finance	0.700	0.461	0.022	0.028	0.025	0.031		
6 Industry Type _{t-1} : Retail & Trade	0.130	0.335	-0.023	0.105**	-0.121**	-0.024	-0.576**	
7 Industry Type _{t-1} : Manufacturing	0.110	0.319	-0.052	-0.112**	0.087**	-0.007	-0.544**	-0.139**
8 Academic Performance	3.207	0.536	0.093**	0.051	-0.062*	-0.034	-0.005	0.108**
9 Cognitive Ability	10.923	0.577	0.014	0.136**	-0.054*	-0.038	-0.052	0.083**
10 Bachelor's Degree	0.664	0.473	-0.027	0.183**	-0.019	-0.008	-0.055*	0.110**
11 Public College	0.620	0.486	-0.107**	-0.057*	0.010	0.022	-0.076**	0.030
12 Sex: Male	0.689	0.464	0.028	0.082**	-0.009	0.037	0.159**	-0.094**
13 Ethnicity: White	0.588	0.493	-0.022	0.122**	-0.053	-0.003	0.066*	0.032
14 Ethnicity: African-American	0.236	0.425	0.036	-0.054*	0.123**	-0.042	-0.088**	-0.055*
15 Extraversion	5.260	1.318	-0.011	0.006	0.004	0.043	-0.102**	0.061*
16 Emotional Resilience	5.760	1.214	0.051*	0.007	-0.032	0.031	-0.077**	0.042
17 Cooperative Education Experience	0.053	0.225	0.050*	0.000	0.022	-0.014	-0.002	0.024
18 Internship Experience	0.450	0.498	0.124**	-0.007	0.005	0.030	0.027	-0.025
19 Mentorship Experience	0.387	0.488	0.160**	0.017	-0.045	-0.017	-0.028	0.008
20 Job Shadowing Experience	0.063	0.243	-0.026	-0.028	0.043	-0.024	0.020	-0.013

Correlations are based on lagged N = 1358; SD = Standard Deviation; * $p < 0.05$; ** $p < 0.01$.

Table 7: Descriptive Statistics and Correlations

	7	8	9	10	11	12	13
1 IT Career Persistence							
2 Working Hours $t-1$							
3 Job Satisfaction $t-1$							
4 Wage $t-1$							
5 Industry Type $t-1$: Professional, Business or Finance							
6 Industry Type $t-1$: Retail & Trade							
7 Industry Type $t-1$: Manufacturing							
8 Academic Performance	-0.040						
9 Cognitive Ability	-0.019	0.072**					
10 Bachelor's Degree	-0.009	0.086**	0.318**				
11 Public College	0.099**	-0.070**	0.109**	-0.040			
12 Sex: Male	-0.045	0.000	0.036	-0.011	-0.003		
13 Ethnicity: White	-0.045	0.070**	0.356**	0.135**	0.063**	0.183**	
14 Ethnicity: African-American	0.037	-0.041	-0.331**	-0.101**	0.017	-0.149**	-0.672**
15 Extraversion	0.075**	-0.057*	-0.070**	-0.040	-0.083**	-0.002	-0.187**
16 Emotional Resilience	0.036	0.041	0.097**	0.027	0.013	0.065**	0.011
17 Cooperative Education Experience	0.017	0.132**	-0.013	0.007	0.017	0.066**	-0.031
18 Internship Experience	0.048	0.102**	0.028	0.143**	0.019	0.079**	0.001
19 Mentorship Experience	0.036	0.165**	0.013	0.105**	-0.032	-0.037	-0.022
20 Job Shadowing Experience	-0.021	-0.067**	-0.108**	-0.116**	0.057*	-0.064**	-0.096**

Correlations are based on lagged N = 1358; SD = Standard Deviation; * $p < 0.05$; ** $p < 0.01$.

Table 7: Descriptive Statistics and Correlations (Continued)

	14	15	16	17	18	19
1 IT Career Persistence						
2 Working Hours $t-1$						
3 Job Satisfaction $t-1$						
4 Wage $t-1$						
5 Industry Type $t-1$: Professional, Business or Finance						
6 Industry Type $t-1$: Retail & Trade						
7 Industry Type $t-1$: Manufacturing						
8 Academic Performance						
9 Cognitive Ability						
10 Bachelor's Degree						
11 Public College						
12 Sex: Male						
13 Ethnicity: White						
14 Ethnicity: African-American						
15 Extraversion	0.156**					
16 Emotional Resilience	0.029	0.091**				
17 Cooperative Education Experience	0.100**	0.024	0.052*			
18 Internship Experience	0.029	-0.054*	0.044	-0.014		
19 Mentorship Experience	0.112**	-0.013	-0.022	-0.070	0.391**	
20 Job Shadowing Experience	-0.005	-0.083**	-0.003	-0.006	-0.039	-0.034

Correlations are based on lagged N = 1358; SD = Standard Deviation; * $p < 0.05$; ** $p < 0.01$.

Table 8: Results of the Tobit Panel Regression

		Dependent Variable: IT Career Persistence				
		Model I				
Control Variables		Estimate	se	t value	[95% CI]	
Intercept	β_0	-1.839	3.499	-0.530	-8.698	5.019
Working Hours _{t-1}	β_1	0.034***	0.010	3.450	0.015	0.053
Job Satisfaction _{t-1}	β_2	0.052	0.075	0.690	-0.095	0.198
Wage Rate _{t-1}	β_3	0.001	0.001	1.620	0.000	0.003
Industry Type: Professional, Business or Finance _{t-1}	β_4	-1.221**	0.377	-3.240	-1.960	-0.483
Industry Type: Retail & Trade _{t-1}	β_5	-0.449	0.431	-1.040	-1.293	0.396
Industry Type: Manufacturing _{t-1}	β_6	-0.456	0.428	-1.060	-1.294	0.383
Academic Performance	β_7	0.697*	0.295	2.370	0.120	1.274
Cognitive Ability	β_8	0.127	0.309	0.410	-0.478	0.732
Bachelor's Degree	β_9	-0.362	0.349	-1.040	-1.045	0.321
Public College	β_{10}	0.577	0.350	1.650	-0.110	1.264
Sex: Male	β_{11}	-0.156	0.443	-0.350	-1.025	0.713
Ethnicity: White	β_{12}	0.184	0.509	0.360	-0.814	1.183
Ethnicity: African-American	β_{13}	-0.634	0.327	-1.940	-1.274	0.007
Extraversion	β_{14}	-0.139	0.118	-1.180	-0.370	0.092
Emotional Resilience	β_{15}	0.102	0.134	0.760	-0.162	0.365
Wald χ^2 (15)		239.980				
Log Likelihood		-3288.4913				

* $p < 0.05$; ** $p < 0.01$ *** $p < 0.001$; se denotes robust standard errors; CI denotes the confidence interval of the estimates.

t-1 one-year lagged variable

Table 8: Results of the Tobit Panel Regression (Continued)

Dependent Variable: IT Career Persistence						
Control Variables		Model II				
		Estimate	se	t value	[95% CI]	
Intercept	β_0	-0.551	1.626	-0.340	-3.740	2.638
Working Hours _{t-1}	β_1	0.009	0.010	0.940	0.010	0.029
Job Satisfaction _{t-1}	β_2	0.044	0.077	0.570	-0.108	0.196
Wage Rate _{t-1}	β_3	0.000	0.001	0.020	-0.002	0.002
Industry Type: Professional, Business or Finance _{t-1}	β_4	-0.768*	0.299	-2.570	-1.354	-0.182
Industry Type: Retail & Trade _{t-1}	β_5	-0.777*	0.346	-2.240	-1.456	-0.097
Industry Type: Manufacturing _{t-1}	β_6	-1.047**	0.346	-3.030	-1.726	-0.368
Academic Performance	β_7	0.417**	0.134	3.120	0.155	0.679
Cognitive Ability	β_8	0.191	0.138	1.390	-0.079	0.462
Bachelor's Degree	β_9	-0.435**	0.159	-2.730	-0.747	-0.123
Public College	β_{10}	-0.668***	0.147	-4.550	-0.956	-0.380
Sex: Male	β_{11}	-0.218	0.161	-1.350	-0.098	0.534
Ethnicity: White	β_{12}	-0.237	0.202	-1.170	-0.632	0.159
Ethnicity: African-American	β_{13}	-0.043	0.237	-0.180	-0.508	0.423
Extraversion	β_{14}	-0.086	0.055	-0.420	-0.194	0.023
Emotional Resilience	β_{15}	0.100	0.059	0.810	-0.016	0.216
Explanatory Variables						
High Direct Experience H3						
Cooperative Education Experience	β_{16}	0.531	0.300	1.770	-0.058	1.120
Internship Experience	β_{17}	0.500**	0.155	3.220	0.196	0.805
Mentorship Experience	β_{18}	0.845***	0.158	5.340	0.534	1.155
Low Direct Experience H4						
Job Shadowing Experience	β_{19}	-0.290	0.294	-0.980	-0.867	0.288
Wald χ^2 (19)				339.020		
Log Likelihood				-3657.568		

* $p < 0.05$; ** $p < 0.01$ *** $p < 0.001$; se denotes robust standard errors; CI denotes the confidence interval of the estimates.

t-1 one-year lagged variable

Hypothesis 4 predicted a positive relationship between low direct experience of college-based career intervention and IT career persistence. Results from Table 8 (Model II) indicate that the relationship between job shadowing experience and IT career persistence is negative but not significant ($\beta_{19} = -0.290, t = -0.980, n.s.$). Hypothesis 4 is not supported.

Post Hoc Analysis

It is well documented that males persist longer in STEM careers than females (Ahuja, 2002; Duxbury & Mills, 1989). The gendered persistence of STEM careers is even more pronounced in the early stages of careers. The early career stage coincides with the stage in women's lives where they perceive the demands of STEM careers to be at odds with their family orientation (Ahuja, 2002; Duxbury & Mills, 1989). To avoid work and family-life conflict, women tend to withdraw from STEM careers and instead pursue family life (Ahuja, 2002).

Career interventions provide occupation-specific skills and experiences that strengthen the professional identities or career orientations of individuals (Brooks, Cornelius, Greenfield, & Joseph, 1995). For female graduates, who are expected to ascribe to a family orientation in early careers, a strengthened STEM career orientation becomes even more salient. I expect female graduates with a salient STEM career orientation to respond or reaffirm their STEM career orientation by pursuing STEM careers as opposed to family-life.

In essence, a strengthened STEM career orientation enabled by college-based career interventions could supplant the family-life orientation of female

STEM graduates. In view of this, I conducted a post hoc analysis to investigate the potential interaction effect of sex on the relationship between high and low direct experiences gained from college-based career interventions and IT career persistence.

Table 9 presents the results of the post hoc analysis. Model I of Table 9 presents the results of the interaction effect between high direct experience and sex on IT career persistence. The results indicate that the interaction between cooperative education experience and sex is positive but not significant ($\beta_c = 0.608, t = 0.770, ns$). The interaction between internship experience and sex is negative and significant ($\beta_i = -0.235, t = -2.140, p < 0.05$). The interaction between mentorship experience and sex is negative and significant ($\beta_m = -0.409, t = -2.160, p < 0.05$). Figures 5 and 6 presents the graphs of the significant interactions.

Model II of Table 9 presents the results of the interaction effect between low direct experience and sex on IT career persistence. The results indicate that the interaction between job shadowing experience and sex is positive and significant ($\beta_j = 1.828, t = 2.970, p < 0.01$). Figure 7 presents the graph of the interaction.

Table 9: Results of the Post hoc Analysis

Dependent Variable: IT Career Persistence						
Control Variables		Model I				
		Estimate	se	t value	[95%CI]	
Intercept	β_0	-0.993	1.639	-0.610	-4.208	2.221
Working Hours _{t-1}	β_1	0.008	0.010	0.780	-0.012	0.028
Job Satisfaction _{t-1}	β_2	0.017	0.078	0.220	-0.136	0.171
Wage Rate _{t-1}	β_3	0.000	0.001	0.170	-0.002	0.002
Industry Type: Professional, Business or Finance _{t-1}	β_4	-0.656*	0.303	-2.160	-1.250	-0.062
Industry Type: Retail & Trade _{t-1}	β_5	-0.684	0.353	-1.940	-1.376	0.008
Industry Type: Manufacturing _{t-1}	β_6	-0.835**	0.350	-2.380	-1.523	-0.148
Academic Performance	β_7	0.580***	0.134	4.320	0.317	0.844
Cognitive Ability	β_8	0.225	0.140	1.600	-0.050	0.500
Bachelor's Degree	β_9	-0.279	0.160	-1.740	-0.593	0.035
Public College	β_{10}	-0.702***	0.149	-4.720	-0.994	-0.411
Sex: Male	β_{11}	0.221	0.165	1.340	-0.103	0.545
Ethnicity: White	β_{12}	-0.144	0.203	-0.710	-0.542	0.253
Ethnicity: African-American	β_{13}	0.240	0.238	1.010	-0.227	0.707
Extraversion	β_{14}	-0.099	0.056	-1.780	-0.209	0.010
Emotional Resilience	β_{15}	0.095	0.060	1.590	-0.022	0.213
Cooperative Education Experience	β_{16}	0.028	0.720	0.040	-1.383	1.440
Explanatory Variables						
Cooperative Education Experience x Sex	β_c	0.608	0.793	0.770	-0.946	2.163
Wald χ^2 (17)				249.170		
Log Likelihood				-3287.930		

* $p < 0.05$; ** $p < 0.01$ *** $p < 0.001$; se denotes robust standard errors; CI denotes the confidence interval of the estimates.

t-1 one-year lagged variable

Table 9: Results of the Post hoc Analysis

Dependent Variable: IT Career Persistence						
Control Variables		Model I				
		Estimate	se	t value	[95% CI]	
Intercept	β_0	-1.160	1.624	-0.710	-4.345	2.026
Working Hours _{t-1}	β_1	0.010	0.010	0.960	-0.010	0.029
Job Satisfaction _{t-1}	β_2	0.014	0.078	0.180	-0.139	0.167
Wage Rate _{t-1}	β_3	0.000	0.001	0.010	-0.002	0.002
Industry Type: Professional, Business or Finance _{t-1}	β_4	-0.753**	0.301	-2.500	-1.343	-0.163
Industry Type: Retail & Trade _{t-1}	β_5	-0.744*	0.348	-2.130	-1.428	-0.060
Industry Type: Manufacturing _{t-1}	β_6	-1.006**	0.349	-2.880	-1.691	-0.321
Academic Performance	β_7	0.548	0.133	4.130	0.288	0.808
Cognitive Ability	β_8	0.212	0.139	1.530	-0.060	0.484
Bachelor's Degree	β_9	-0.395**	0.160	-2.470	-0.709	-0.082
Public College	β_{10}	-0.700***	0.148	-4.740	-0.989	-0.410
Sex: Male	β_{11}	0.298	0.213	1.400	-0.120	0.716
Ethnicity: White	β_{12}	-0.113	0.202	-0.560	-0.510	0.284
Ethnicity: African-American	β_{13}	0.210	0.235	0.900	-0.250	0.670
Extraversion	β_{14}	-0.078	0.056	-1.410	-0.187	0.031
Emotional Resilience	β_{15}	0.095	0.060	1.580	-0.023	0.213
Internship Experience	β_{17}	0.971***	0.270	3.590	0.440	1.501
Explanatory Variables						
Internship Experience x Sex	β_i	-0.235*	0.503	-2.140	-0.861	0.392
Wald χ^2 (17)				258.640		
Log Likelihood				-3283.041		

* $p < 0.05$; ** $p < 0.01$ *** $p < 0.01$; se denotes robust standard errors; CI denotes the confidence interval of the estimates.

t-1 one-year lagged variable

Table 9: Results of the Post hoc Analysis

Dependent Variable: IT Career Persistence						
Control Variables		Model I				
		Estimate	se	t value	[95% CI]	
Intercept	β_0	-0.997	1.618	-0.620	-4.170	2.177
Working Hours _{t-1}	β_1	0.008	0.010	0.800	-0.012	0.027
Job Satisfaction _{t-1}	β_2	0.043	0.078	0.550	-0.110	0.195
Wage Rate _{t-1}	β_3	0.000	0.001	0.100	-0.002	0.002
Industry Type: Professional, Business or Finance _{t-1}	β_4	-0.678*	0.299	-2.270	-1.264	-0.092
Industry Type: Retail & Trade _{t-1}	β_5	-0.701*	0.347	-2.020	-1.381	-0.020
Industry Type: Manufacturing _{t-1}	β_6	-0.929**	0.346	-2.690	-1.608	-0.251
Academic Performance	β_7	0.460***	0.133	3.460	0.199	0.721
Cognitive Ability	β_8	0.205	0.138	1.490	-0.066	0.476
Bachelor's Degree	β_9	-0.379*	0.159	-2.390	-0.691	-0.068
Public College	β_{10}	-0.657***	0.147	-4.470	-0.946	-0.369
Sex: Male	β_{11}	0.468*	0.210	2.230	0.057	0.879
Ethnicity: White	β_{12}	-0.213	0.201	-1.060	-0.607	0.181
Ethnicity: African-American	β_{13}	0.019	0.235	0.080	-0.442	0.481
Extraversion	β_{14}	-0.090	0.055	-1.630	-0.198	0.018
Emotional Resilience	β_{15}	0.111	0.059	1.870	-0.005	0.227
Mentorship Experience	β_{18}	1.336***	0.267	5.000	0.813	1.860
Explanatory Variables						
Mentorship Experience x Sex	β_m	-0.409*	0.189	-2.160	-1.025	0.207
Wald χ^2 (17)				264.32		
Log Likelihood				-3280.141		

* $p < 0.05$; ** $p < 0.01$ *** $p < 0.01$; se denotes robust standard errors; CI denotes the confidence interval of the estimates.

t-1 one-year lagged variable

Table 9: Results of the Post hoc Analysis

Dependent Variable: IT Career Persistence						
Control Variables		Model II				
		Estimate	se	t value	[95%CI]	
Intercept	β_0	-1.304	1.650	-0.790	-4.541	1.933
Working Hours _{t-1}	β_1	0.008	0.010	0.800	-0.012	0.028
Job Satisfaction _{t-1}	β_2	0.006	0.079	0.080	-0.148	0.160
Wage Rate _{t-1}	β_3	0.000	0.001	0.170	-0.002	0.002
Industry Type: Professional, Business or Finance _{t-1}	β_4	-0.663**	0.302	-2.190	-1.256	-0.070
Industry Type: Retail & Trade _{t-1}	β_5	-0.709**	0.351	-2.020	-1.398	-0.020
Industry Type: Manufacturing _{t-1}	β_6	-0.899**	0.350	-2.570	-1.586	-0.212
Academic Performance	β_7	0.646***	0.134	4.830	0.384	0.909
Cognitive Ability	β_8	0.232	0.140	1.650	-0.043	0.507
Bachelor's Degree	β_9	-0.280	0.160	-1.750	-0.594	0.033
Public College	β_{10}	-0.669***	0.149	-4.490	-0.961	-0.377
Sex: Male	β_{11}	0.120	0.168	0.710	-0.210	0.450
Ethnicity: White	β_{12}	-0.119	0.204	-0.580	-0.519	0.282
Ethnicity: African-American	β_{13}	0.309	0.238	1.300	-0.158	0.776
Extraversion	β_{14}	-0.097	0.056	-1.720	-0.207	0.013
Emotional Resilience	β_{15}	0.115	0.060	1.910	-0.003	0.233
Job Shadowing Experience	β_{19}	-1.396**	0.483	-2.890	-2.342	-0.449
Explanatory Variables						
Job Shadowing Experience x Sex	β_j	1.828**	0.616	2.970	0.620	3.035
Wald χ^2 (17)				250.080		
Log Likelihood				-3287.418		

* $p < 0.05$; ** $p < 0.01$ *** $p < 0.001$; se denotes robust standard errors; CI denotes the confidence interval of the estimates.

t-1 one-year lagged variable

Figure 5: Internship Experience and Sex Interaction

Figure 6: Mentorship Experience and Sex Interaction

Figure 7: Job Shadowing Experience and Sex Interaction

Discussion

The current research examines the role college-based career interventions play in determining (1) initial IT employment and (2) IT career persistence. College-based career interventions comprise of high and low direct experiences. High direct experience of college-based career intervention includes cooperative education, internship and mentorship. Low direct experience of college-based career intervention includes job shadowing.

Career Interventions and Initial IT Employment

Human capital theory (Becker, 1975) predicts that occupational training raises employee productivity on the job. Participation in occupational training programs prompts favorable employment outcomes including increased levels of employability (Smith, 2010). College-based career interventions prepare IT graduates with productive work experience, work values and norms which raise

their levels of employability and thus increase the likelihood of finding IT employment at graduation.

High direct and low direct experiences of career intervention should therefore increase the likelihood of initial IT employment. Consistent with the predictions of human capital theory (Becker, 1975), I find support for the prediction that high direct experience gained from college-based career intervention increases the likelihood of initial IT employment. Specifically, cooperative education, internship and mentorship experiences significantly increase the likelihood of initial IT employment. This finding is consistent with prior research which has demonstrated that participation in some form of experiential job training program ranks high on recruiters' criteria for selecting new graduates (Zhao & Liden, 2011).

I do not find support for the prediction that low direct experience gained from career intervention increases the likelihood of initial IT employment. Specifically, I do not find support for the prediction that job shadowing experience increases the likelihood of initial IT employment. A possible explanation for the nonsignificant finding could be that IT employers do not consider job shadowing as an effective intervention for transferring task-specific IT skills. The personnel training literature (Goldstein, 1980; Manz & Sims, 1981) provides a useful perspective in explaining why job shadowing may not be effective for transferring IT skills.

Job shadowing is more suited to aspirants to occupations for which motor skills acquisition and reproduction form an instructive component of the

job-learning and skills development process (Gioia & Manz, 1985; Goldstein, 1980; Manz & Sims, 1981). But IT work requires more than just motor skills. IT work requires problem solving and analytical skills. Job shadowing, therefore, may be of limited effectiveness in transferring skills in knowledge-based occupations including the IT profession.

Career Interventions and IT Career Persistence

By participating in career interventions, IT graduates acquire IT-specific skills, assimilate professional norms and values and thereby form a professional identity in IT. The concept of identity salience (Callero, 1985; Stryker, 1980; Turner, 1978) predicts that IT graduates who participate in college-based career interventions would persistently pursue IT careers to reaffirm and validate the professional identities they form in IT.

High and low direct experiences of college-based career interventions should prompt persistence in IT careers. Consistent with the arguments drawn from the human capital literature and identity theory, the results provide partial support for the prediction that high direct experience of college-based career intervention increases persistence in IT careers. Specifically, internship and mentorship experiences are positively associated with IT career persistence.

The finding validates earlier research which investigates the role professional associations play in retaining young computing professionals (Umapathy & Ritzhaupt, 2011). Umapathy and Ritzhaupt (2011) contend that computing professional associations may increase retention of young computing professionals by incorporating mentorship and internship programs.

Senior computing professionals support junior computing professionals with their professional development and aid them in forging a professional identity in IT (Umapathy & Ritzhaupt, 2011).

Surprisingly, I do not find evidence for the prediction that cooperative education experience is positively associated with IT career persistence. A possible explanation for the lack of evidence could stem from the relative few number of cooperative education graduates in the sample. Of the 318 respondents that make up the sample, approximately 5% enrolled in a cooperative education program. It is conceivable to argue that there is not enough statistical power to generate a significant effect. The results indicate a narrower lower confidence interval $[-0.058, 0]$ relative to the wider positive upper confidence interval $[0, 1.120]$. This alludes to the possibility that the effect of cooperative education experience on IT career persistence may have been significantly positive with a larger sample.

I do not find evidence for the prediction that job shadowing experience is positively associated with IT career persistence. Interestingly, a post hoc analysis uncovered that female IT graduates who participate in job shadowing programs persist less in IT careers. To contrast, the post hoc analysis indicated that female IT graduates who participate in internship and mentorship programs persist in IT careers. The contrasting finding could be due to the difference in the levels of occupation-specific skills offered by high and low direct experiences of career interventions.

Female IT graduates require greater socialization into the IT profession because the demanding nature of IT work often encroaches into their family-life orientation (Ahuja, 2002). Job shadowing programs provide little in terms of practical skills required for professional development and orchestrating an occupational identity in IT. This may explain why female IT graduates who participate in job shadowing programs persist less in early IT careers.

In contrast, high direct experience gained from college-based career interventions provides female IT graduates with practical IT skills and self-efficacy much needed for thriving in the IT occupational environment (Joseph, 2008a). Thus, female IT graduates who participate in internship and mentorship programs are emboldened, skill-wise. They develop a professional identity and are thereby motivated to pursue IT careers in the early career stage.

Implications for Research

The current research has important implications for turnaway and IT human capital research. For IT human capital research, the current research extends existing studies (e.g. Ang et al., 2002; Mithas & Krishnan, 2008) that have examined IT and firm-specific experience as determinants of IT career outcomes. The current research is novel in introducing career intervention experience into the literature on human capital determinant of IT career outcomes.

For turnaway research, the existing studies (e.g. Joseph et al. 2012) draw on distributive justice theory to argue that relative pay gap between IT professionals influences persistence in IT careers. The current research departs

from the existing studies. I draw arguments from the human capital literature and identity theory and predict that career intervention experiences are associated with increased levels of persistence in IT careers.

Current research frames career interventions experiences as high direct and low direct experiences. This framing brings a finer understanding of the efficacies of different modalities of career interventions. Future research should extend the current study by empirically examining the potential contrast in efficacies between high and low direct experiences of career interventions in regards to task performance in IT.

Further, the finding that women who participate in job shadowing programs persist less in IT careers could be an indication that job shadowing programs do not strengthen the self-efficacy of women to thrive in STEM careers. Future research should examine whether levels of IT career self-efficacy differ across women participating in different modalities of career interventions.

Implications for Practice

The current research has important implications for institutions of higher learning (IHL), early career IT professionals and IT graduates as well policy makers. First, IHLs may benefit from the findings of the study in educating and elevating students' awareness about career skills development and IT employability at graduation.

Given budgetary constraints, findings of the study could inform administrators of IHLs of the relative efficacies of experiential and vicarious

modalities of career interventions in determining IT employability. For IT students, the results reported in the current study would encourage them to participate in career interventions to facilitate entry into the IT profession.

Second, policymakers should be aware that career interventions enable newly-minted IT graduates to persist in early IT careers. Public agencies that have the responsibility of ensuring a sustainable flow of IT talents to meet the current and future demand for IT manpower may benefit from the results of our study. The results could inform policy positions that are based on IT attrition concerns.

Conclusion

The current research serves two goals. First, I examined the relationship between college-based career interventions and initial IT employment. Specifically, I examined the relationships between high and low direct experiences gained from college-based career intervention and initial IT employment. The results show that cooperative education, internship and mentorship experiences increase the likelihood of initial IT employment. I do not find support for the prediction that job shadowing experience increases the likelihood of initial IT employment.

Second, I examined the relationships between high and low direct experiences gained from college-based career interventions, and IT career persistence. Specifically, I predicted that high and low direct experiences of career interventions raise persistence in IT careers. The results indicate that internship and mentorship experiences are positively related to IT career

persistence. I do not find support for the predicted positive effects of cooperative education and job shadowing experiences on IT career persistence.

Appendix I

Figure 8: Log Survival Plot

Appendix II

Multilevel Multiprocess Model Estimation (MLMP)

Equation 5 is a survival model that expresses log survival times¹ or unemployment period as a linear function of college-based career interventions.

$$\log t = \beta_0 + \beta_1 CBCI + \varepsilon_1 \quad \text{Equation [5]}$$

$$CBCI = \pi_0 + \pi_1 GHealth + \varepsilon_2 \quad \text{Equation [6]}$$

where $Cov(GHealth, \varepsilon_1) = 0$ and $Cov(GHealth, CBCM) \neq 0$

Where t denotes the survival time; ε is the residual term; $CBCI$ is the endogenous variable i.e. College-Based Career Intervention; $GHealth$ is the general health status of respondents measured on a 5-point Likert Scale (reversed coded) in the NLSY97 data (“1” = Poor ... “5” = Excellent).

To the extent that college-based career interventions are potentially endogenous, then college-based career interventions (CBCI) are correlated with the residual term ε_1 . As earlier articulated, this produces inconsistent estimates and standard errors (Lillard, 1993). To correct for this bias, an instrumental variable must be introduced into the estimation procedure (Roodman, 2011). A valid instrument must be: (1) relevant – must predict the endogenous variable and (2) exogenous – needs to be uncorrelated with the residual term (Stock & Watson, 2003).

¹ STATA’s CMP module supports only lognormal survival models but not exponential models (Bartus, 2012). I am impelled by this constraint to examine only lognormal survival models. Other software packages do not support MLMP estimations.

I estimated the influence of college-based career interventions on the unemployment period by using general health status as an instrument for college-based career interventions in a survival model. There is evidence to suggest that school programs that integrate classroom-based learning with career development programs cause more stress in participants (Jogaratnam & Buchanan, 2004; Rodolfa, Kraft, & Reilley, 1988).

Considering this evidence, I expect that respondents would consider the state of their general health before participating in any of the college-based career intervention programs. Essentially, the general health status of respondents at the time of enrolling should explain participation in college-based career interventions to an extent. There is however no *ex ante* reason to assume that the general health status of respondent at the time of enrolling into any of the college-based career interventions is correlated with the unemployment period. For the MLMP estimator, the probability of participating in a college-based career intervention (equation 6) is jointly modeled and estimated with the survival model (equation 5) using the CMP module in STATA (Bartus, 2012; Roodman, 2017).

Results of the MLMP Estimation

Before reporting the results, it is important to note that the interpretation of the results from Table 10 are consistent with the interpretation of the initial results (Table 6) only when the respective estimates have opposite signs. This is because the unemployment period and the hazard risk to initial IT

employment are inversely related; i.e. the shorter the unemployment period, the higher the hazard risk or likelihood of initial IT employment and vice versa.

Results of the endogenous model (Model I), obtained by estimating equation 4 separately, is consistent with the initial results. The relationships between Cooperative Education ($\beta = -0.197, p < 0.05$), Internship ($\beta = -0.068, p < 0.05$), and Mentorship Experience ($\beta = -0.362, p < 0.001$) and the unemployment period are negative and significant. The relationship between Job Shadowing Experience and the unemployment period is positive but not significant ($\beta = 0.002, n. s.$).

Appendix III

Table 10: Results of the Multilevel Multiprocess (MLMP) Model Estimation

Dependent Variable: Unemployment Period										
Control Variables	Separate Model				Joint Models					
	Model I		Model II		Model III		Model IV		Model V	
	Estimate	se	Estimate	se	Estimate	se	Estimate	se	Estimate	se
Intercept	4.127***	0.635	4.195***	0.753	4.280***	0.741	4.234***	0.648	4.277***	0.760
Unemployment Rate	-0.012	0.016	-0.011	0.017	-0.011	0.017	-0.015	0.017	-0.013	0.017
Region: North Central	0.055	0.069	0.085	0.071	0.094	0.072	0.053	0.067	0.090	0.070
Region: South	0.055	0.063	0.068	0.064	0.068	0.065	0.056	0.063	0.069	0.066
Region: West	-0.005	0.026	0.001	0.026	0.005	0.027	-0.002	0.025	0.004	0.028
Urban	-0.305**	0.102	-0.285*	0.111	-0.308**	0.111	-0.293**	0.099	-0.288**	0.110
Sex: Male	-0.029	0.052	-0.019	0.055	-0.023	0.056	-0.038	0.053	-0.022	0.056
Race: White	0.051	0.060	0.028	0.067	0.036	0.068	0.043	0.061	0.028	0.069
Race: African-American	-0.129	0.078	-0.188*	0.086	-0.194*	0.086	-0.144	0.079	-0.194*	0.087
Socioeconomic Status	-0.0514*	0.023	-0.063**	0.024	-0.067**	0.024	-0.0530*	0.024	-0.065**	0.025
Public College	-0.063	0.052	-0.081	0.055	-0.079	0.055	-0.066	0.052	-0.082	0.055
Bachelor's Degree	-0.023	0.054	-0.020	0.059	-0.027	0.060	-0.016	0.056	-0.020	0.058
Academic Performance	-0.204***	0.051	-0.212***	0.055	-0.224***	0.054	-0.215***	0.051	-0.221***	0.053
Cognitive Ability	0.059	0.049	0.057	0.053	0.053	0.053	0.056	0.050	0.055	0.053
Median Wage Rate	0.001	0.001	0.001	0.000	0.001	0.000	0.001	0.000	0.001	0.000
Duration of Career-Based College Modality	-0.098***	0.015	-0.117***	0.014	-0.124***	0.016	-0.098***	0.013	-0.119***	0.014
Explanatory Variables										
High Direct Experience (H1)										
Cooperative Education Experience	-0.197*	0.090	-0.143*	0.066						
Internship Experience	-0.068*	0.030			-0.147**	0.060				
Mentorship Experience	-0.362***	0.073					-0.296**	0.108		
Low Direct Experience (H2)										
Job Shadowing Experience	0.002	0.140							0.080	0.141
Probit Model										
Intercept			-2.982***	0.745	0.081	0.180	0.208	0.184	-1.655***	0.313
General Health Status			0.323*	0.164	0.095*	0.042	0.266**	0.090	0.054*	0.020
General Health Status (Marginal Effects)			0.034*	0.016	0.038*	0.017	0.098**	0.033	0.077*	0.034
AIC	1017.688		1169.374		1440.395		1405.127		1172.512	
$\rho_{\text{CBCL, GHealth}}$			0.102		0.160		0.166		0.134	

se denotes robust standard errors; $\rho_{\text{CBCL, GHealth}}$ denotes the correlation between the College-Based Career Intervention and General Health Status; * $p < 0.05$; ** $p < 0.01$ *** $p < 0.001$;

Models II, III, IV and V are the joint models obtained by jointly estimating equations 5 and 6 and thereby adjusting for endogeneity. Results of Models II, III, IV and V are consistent with the initial results (Table 6). Results of Model II indicate that the relationship between cooperative education experience and unemployment period is negative and significant ($\beta = -1.043, p < 0.05$). For Model III, the relationship between Internship Experience and unemployment period is negative and significantly different than zero ($\beta = 0.147, p < 0.05$).

Results of Model IV indicate that the relationship between Mentorship Experience and unemployment period is negative and significantly different than zero ($\beta = -0.295, p < 0.05$). Model V indicate that the relationship between Job Shadowing Experience and unemployment period is positive but not significant ($\beta = 0.080, n.s.$). General Health Status appears to be good instrument for cooperative education, internship, mentorship and job shadowing experience.

CHAPTER 3

An Empirical Examination of the Value of Formal IT-oriented Degrees

Introduction

The traditional pathway to an information technology (IT) career begins with an undergraduate enrollment in computer science or an IT-oriented degree at a cost. In the United States (US), the annual cost of an undergraduate degree in computer science is estimated at \$39000 (IPEDS, 2016). Considering that IT, in and of itself, has lowered the barriers to learning employable IT skills, the investments made into attaining IT degrees raise important questions about the value of IT degrees.

The popular press has taken a dim view of IT degrees and accentuated the concerns about the value of IT degrees. Mashable, a technology news blog, published an article titled “Warning: A computer science degree may be a waste of your time” (Mashable, 2014). Other publications argue that IT degree requirements are no longer essential for improving employment prospects and attracting tangible market rewards (Fortune, 2015; InfoWorld, 2012; Wall Street Journal, 2015).

Additionally, more than a third of US IT professionals have not attained an IT degree and the number of non-IT graduates entering the IT workforce continues to grow (Salzman et al., 2013). The increase in the number of non-IT graduates in the IT workforce is attributed to the increasing demand for IT labor and the relative shortage in the supply of IT graduates. The pressure to meet the demand for IT labor has translated into less concern for hiring on IT

qualifications and more willingness to recruit from nontraditional sources including non-IT graduates (Cisco Systems Inc., 2008; Moore, Yager, Sumner, & Crow, 2001).

The cost of attaining IT degrees, the popular press' dim view of IT degrees and the prevalence of non-IT graduate entrants to the IT workforce culminate in the need to inquire whether IT degrees are more valuable than non-IT degrees. Do IT degrees command a higher wage premium in the IT labor market?

Two streams of research offer important insights into the value of IT human capital. The first stream has demonstrated that higher levels of education, often operationalized by the hierarchical gradation of education credentials (e.g. bachelor's and postgraduate degrees), is associated with increased levels of compensation (Ang, Slaughter, & Yee Ng, 2002; Levina & Xin, 2007; Mithas & Krishnan, 2008). However, the hierarchical gradation of education credentials poses a theoretical challenge. The hierarchical gradation of educational credential is agnostic to the distinction between occupation specific and non-occupation specific or general human capital types (Becker, 1975).

The lack of distinction conceals the possibility that occupation specific and general human capital types may differentially predict compensation levels (Shaw, 1984). In addressing this limitation of the extant studies, the current research disentangles the value of IT-specific human capital from non-IT human capital by jointly examining the value of IT and non-IT degrees.

In addition, I provide a more nuanced understanding of the value of IT-specific human capital by examining the wage growth rates of IT and non-IT graduates in early IT careers. Wage growth is contemporaneous with productivity growth. Thus, the question of whether there is a difference in the wage growth rates of IT and non-IT graduates is a central element to scholarly theorizing on employee productivity in early tenure of IT careers, which is seldom highlighted in the IT human capital literature.

The second research stream has demonstrated that the value of IT human capital attributes of firm-specific and IT experience varies across industries (Ang, Slaughter, & Yee Ng, 2002; Levina & Xin, 2007; Mithas & Krishnan, 2008). What remains less clear is whether the value of the qualitative aspects of IT human capital including IT degree attainment vary across industries. Accordingly, I add to this stream of research by arguing that educational attributes of IT human capital, denoted as IT degrees, may also be priced differently at the industry level. I expect the industrial pricing of IT degrees to vary for the following reason.

Employers in the high technology industry have a greater need for IT human capital because IT is their core competency. Yet employers in the high technology industry compete with the employers in the low technology industry for IT talent because of the relative shortage in the supply of IT labor. This interplay between the IT human capital needs of institutions in the high and low technology industry and the shortage of IT labor may play a role in determining the value of IT degrees in the market.

Literature Review and Hypotheses Development

There are two parts to this section. First, I review research on IT human capital and present findings related to the value of IT human capital. Second, I present the theory guiding the development of the hypotheses. In developing the hypotheses, I draw largely on human capital theory (Becker, 1975) and synthesize its concepts with theoretical arguments flowing from the literature on education-job matching (Allen & Velden, 2001; Sattinger, 1993) and core competency theory (Hamel & Heene, 1994). Figure 1 presents the theoretical model of the current study.

The Value of IT Human Capital

The broader human capital literature emphasizes the productivity and performance outcomes of human capital endowment and training (Haltiwanger, Lane, & Spletzer, 1999). A review of the literature on IT human capital, however, reveals that considerable studies have investigated the value of IT human capital in the form of economic returns. The studies culminate in two distinct research streams which explain the heterogeneity in IT compensation by using theoretical arguments flowing from the literatures on labor supply and demand.

The first stream, the supply-side perspective of IT human capital, focuses on human capital determinants of IT compensation. The second stream, the demand-side perspective, focuses on institutional pricing of IT human capital or the value of IT human capital in different labor market segments.

The first stream of research (Ang, Slaughter, & Ng, 2002; Joseph et al., 2012; Kim, Mithas, Whitaker, & Roy, 2014; Levina & Xin, 2007; Mithas & Krishnan, 2008; Slaughter, Ang, & Fong Boh, 2007), draws largely on human capital theory. The narrative is that IT professionals possess IT human capital, which distinguishes them from other knowledge professionals (Josefek & Kauffman, 2003). Employers rely on IT human capital to design technology-enabled business processes and execute tasks (Mithas & Krishnan, 2008). IT human capital is firm- and industry-specific, suggesting that it may not be readily transferrable across non-IT domains (Kim et al., 2014; Slaughter et al., 2007).

The value of IT human capital is well documented. Ang, Slaughter and Ng (2002) established that compensation in IT is directly related to human capital endowments of experience and education. Specifically, higher endowments of IT experience and education result in increased levels of compensations. Ang and her colleagues attribute their findings to the productivity-enhancing nature of IT human capital. Higher endowments of experience and education increase productivity in IT, which is valued by employers (Ang, Slaughter, & Ng, 2002; Becker, 1962; Becker, 1975).

Perhaps most comprehensively demonstrating the value of IT human capital, Mithas and Krishnan (2008) disaggregated IT experience into firm-specific experience and general IT experience and disentangled the value of managerial or MBA education from non-managerial education. Firms place greater value on MBAs than non-managerial degrees because of the growing

importance of business and managerial roles in IT work (Mithas & Krishnan, 2008). With regards to experience, the returns associated with general IT experience is greater than the returns associated with firm-specific IT experience. General IT experience is richer and more varied than firm-specific IT experience in that general IT experience encompasses experiences drawn from different work contexts (Mithas & Krishnan, 2008).

The second stream (Ang, Slaughter, & Ng, 2002; Levina & Xin, 2007; Mithas & Krishnan, 2008) of research draws on arguments from neo-institutional theories of the labor market (Bailey & Schwenk, 1980; Brown & Medoff, 1989; Leontaridi, 1998) and attribute the variation in the value of IT human capital to labor market segmentations. Specifically, for-profit and non-profit firms, small and larger firms, and the high and low technology industries price IT human capital differently.

For-profit firms pay higher compensations than non-for profit firms (Ang, Slaughter, & Ng, 2002). Similarly, larger firms pay higher compensations than smaller firms (Ang, Slaughter, & Ng, 2002). For-profit and larger firms have greater financial resources and market power and thus are able to attract and retain talented IT professionals by offering higher wages (Ang, Slaughter, & Ng, 2002).

In the case of the high and low technology industries, there are mixed findings on the value of IT human capital. Some studies show that high technology firms pay higher wages to IT professionals with more experience and education than low technology firms (Ang, Slaughter, & Ng, 2002; Levina,

Xin, & Yang, 2003). High technology firms regard more experienced and educated IT professionals as core employees who are crucial for achieving firm success and profitability.

Another study, however, does not find wage differentials in the high and low technology industries. Mithas and Krishnan (2008) find no evidence to support their hypothesis that dot-com firms compensate experienced IT professionals with higher wages more than less experienced IT professionals. Contrary to expectation, Mithas and Krishnan (2008) find that dot-com firms do not value MBAs more than non-dot-com firms. The lack of evidence is perhaps due to the somewhat homogenous sample, comprising of mid to late career IT professionals (Mean IT experience = 18.1 years; SD = 9 years).

Figure 1: Theoretical Model

The Value of IT and Non-IT Degrees

Human capital theory (Becker, 1962, 2009) draws a distinction between specific and general human capital gained from education. Formal college education prepares individuals with problem-solving, analytical and communication skills that are transferable across all occupations (Becker, 1962, 2009). When considered as a whole, a broad based formal college degree imparts general human capital.

At the college level, individuals major in a field of study with the expectation of entering occupations related to that field (Betts, 1996). The selection of a field of study implies an investment in occupation specific human capital (Becker, 1962; Betts, 1996; Robst, 2007). Investment in occupation specific human capital prepares incumbents with the relevant professional knowledge and skills pertinent to the job roles of their aspiring professions. The match (or mismatch) between the field of study and profession or occupation entered at graduation results in a skills match (or mismatch) which has important productivity implications (Allen & Velden, 2001).

Formal IT degree education remains the traditional way by which IT-specific human capital is developed (Kaarst-Brown & Guzman, 2005). IT degree education is systematic and rigorous in preparing graduates with knowledge, skills and competencies in specialized IT topics including computer programming, systems design and analysis and software development (Khazanchi & Munkvold, 2000). The stock of knowledge, skills and competencies imparted by IT degree education matches with the skills

requirements for IT jobs (Kaarst-Brown & Guzman, 2005; von Dran, 2004). The education-job match facilitates the effective utilization of occupation specific human capital (Allen & van der Velden, 2001). The actual level of work productivity is better realized when the field of study optimally matches with the profession an individual enters.

In contrast, there are new entrants into the IT profession who have attained non-IT degrees (Bartol & Aspray, 2006). There is suboptimal matching between their stock of specific human capital and the skills requirements for IT jobs. A job-education mismatch limits the utilization of accumulated human capital and depresses productivity (Allen & van der Velden, 2001; Sattinger, 1993). In addition, the new IT entrants may have developed IT skills via less formal means including self-learning. Non-formal learning, however, is less systematic and rigorous for imparting specialized IT skills and therefore less productive (Warren Harrison, 2004).

According to human capital theory (Becker, 1975), employers value productive human capital. Therefore, the productivity advantage that IT degree education offers over non-IT degree would result in disparate wages in favor of IT degrees. Accordingly, I hypothesize

Hypothesis 1: IT degrees command higher wages than non-IT degrees.

Wage Growth Rates of IT and Non-IT Degrees

As new entrants gain tenure in IT, they encounter new technologies and must learn new skills while on the job (Joseph, Koh, & Foo, 2010). The process by which new entrants effectively learn new skills while on the job and further

develop their stock of IT-specific human capital depends on their background knowledge in IT. Foundational knowledge plays an instrumental role in an IT professional's capability to assimilate new knowledge and develop new competencies in IT (Boh, Slaughter, & Espinosa, 2007).

IT degrees expedite the learning of new IT concepts and aid in the assimilation of new knowledge while on the job. The expeditious learning trajectory and ease with which IT graduates assimilate new IT knowledge on the job results in a relative increase in productivity growth. Comparatively, non-IT graduates have a slower learning trajectory to assimilate new knowledge and concepts as they encounter new technologies in early IT careers. According to human capital theory (Becker, 1975), the disparity in productivity growths occasioned by IT and non-IT degrees account for observable differences in wage growths. Accordingly, I hypothesize

Hypothesis 2: IT degrees command higher wages than non-IT degrees with increasing tenure in early IT careers.

Institutional Pricing of IT Degrees

Institutions in the high technology industry deploy sophisticated and cutting edge technologies to deliver solutions to their clients. IT is the core competence of institutions in the high technology industry (Ang, Slaughter, & Yee Ng, 2002). Relative to the high technology industry, institutions in the low technology industry deploy IT to provide low level support functions. IT is peripheral and not the core competence of firms in the low technology industry (Ang, Slaughter, & Yee Ng, 2002).

Core competency theory (Hamel & Heene, 1994) posit that the employers in the high technology industry require IT professionals who are highly endowed with IT-specific human capital to successfully man the mission-critical technologies. Thus, IT graduates are more crucial to the competitive strategy of the institutions in the high technology industry than the low technology industry (Ang, Slaughter, & Yee Ng, 2002).

Nonetheless, employers in the high technology industry must still compete with the employers in the low technology industry for IT labor because of the shortage of highly skilled IT talents including IT graduates (Mithas & Krishnan, 2008). It therefore behooves employers in the high technology industry to raise wages to attract and retain IT graduates.

Prior research has demonstrated that higher levels of IT experience commands greater premium in information-intensive industries than non-information intensive industries (Ang, Slaughter, & Yee Ng, 2002; Mithas & Krishnan, 2008). IT experience reflects the level of IT-specific human capital endowment. Consistent with this finding and the theoretical arguments, I expect IT degree, which represents investment in IT-specific human capital required to man mission-critical IT, to be highly valued in the high technology industry relative to the low technology industry.

Hypothesis 3: IT degrees command higher wages in the high technology industry than low technology industry.

Methodology

This section begins with a description of the dataset and the criteria used for constructing the sample. Following, I provide a description of the measures. I present the analytical technique used in analyzing the data.

Data

I used data obtained from the National Longitudinal Survey for Youth 1997 cohort (NLSY97) (US Bureau of Labor Statistics, 2016). The NLSY97 survey is conducted by the National Opinion Research Center, under the auspices of the US Bureau of Labor Statistics (BLS). The NLSY97 project is a longitudinal survey which samples 8984 youthful Americans born between the years of 1980 and 1984 (US Bureau of Labor Statistics, 2016). The first round of the survey was conducted in 1997. Respondents are interviewed on an annual basis. The most recent survey available to the public was conducted in 2012.

The NLSY97 collects information on a broad range of topics including, but not limited to, educational experiences, demography and labor market activities of respondents. Data on educational experiences capture the schooling history of respondents including enrollment and graduation dates, fields of study and education credentials. Demographic data include birth dates, ethnicity and place of residence in the US. Data capturing labor market activities of respondents include variables such as employment history, start and end job dates, wages, firm and job tenure.

The choice of the NLSY97 dataset is based on the following considerations. First, the NLSY97 survey is a nationally representative sample

of the population of US IT professionals. The NLSY uses a probabilistic sampling technique to ensure accurate representation of the US population as defined by socioeconomic and demographic variables including ethnicity, gender and socioeconomic status (Moore, Pedlow, Krishnamurty, Wolter, & Chicago, 2000; US Bureau of Labor Statistics, 2016).

The representativeness of the NLSY97 survey affords me the opportunity to generalize the results and findings to the US IT labor market, which has the largest concentration of technology workers (CompTIA, 2016). Second, the NLSY97 cohort consists of youthful Americans in the early stages of their careers. This is aligned with the main goal of the study, which examines the value of IT in early IT careers. The strength and relevance of the effect of formal college education on labor market outcomes is best demonstrated in early careers; when graduates have just transitioned into the labor market (Kelly & McGrath, 1988; Pascarella, Terenzini, & Feldman, 2005).

Sample Construction

I subjected the universe of 8984 NLSY97 respondents to the following inclusion criteria. First, a respondent qualifies to be included in the sample if he or she held full-time IT jobs for at least three continuous survey years. The BLS defines full-time jobs as jobs that require more than 35 weekly hours.

Singer and Willet (2003) recommend that researchers consider at least three person-period observations when analyzing longitudinal data to adequately model changes in the variables of interest. IT jobs are identified by

the 2002 Standard Occupational Classification (SOC) codes. Table 1 presents the list of the IT jobs.

Second, a respondent qualifies to be included in the sample if he or she completed college education. In the US, a college graduate refers to a person who has attained a bachelor's or associate's degree. Third, a respondent qualifies to be included in the sample if he or she has not engaged in full-time IT employment before enrolling into college education. This criterion is necessary to rule out the potential influence of prior working experience on wages.

Table 1: NLSY97 Job Titles

OCS 2002 Code	Job Title
0110	Computer and Information Systems Manager
1000	Computer Systems Analyst
1010	Computer Programmer
1020	Computer Software Engineer
1040	Computer Support Specialist
1060	Database Administrator
1100	Network and Computer Systems Administrator
1110	Network Systems and Data Communication Analyst
1400	Computer Hardware Engineer

Sample

The final sample consists of 361 respondents. The unit of analysis is the individual. The sample is observed at an annual frequency, beginning in the year a respondent entered IT employment at graduation. The 361 respondents contributed person-period observations that resulted in a panel of 2186 person-period observations. The sample panel is unbalanced because the number of

time period observations is not the same for all individuals in the sample. The year of entry into the IT labor market varies from respondent to respondent.

The 361 respondents consist of 72.3% male (27.7% female); 64.8% are of white ethnicity and the remaining 35.2% are of other ethnicities including African-American, Asian and Hispanic. With regards to the level of education, 44.3% of the final sample have attained associate's degrees and 55.7% have attained bachelor's degrees.

Measures

I provide a description of the variables and the operationalization of the variables in this section. All time-varying independent variables are lagged by a year to mitigate the effect of simultaneity or reverse causality bias between the independent and dependent variables (Singer & Willett, 1991). In addition, lagging increases the predictive power of the independent variables (Kelly & McGrath, 1988). Table 2 provides the definitions of the variables.

Dependent Variable. The dependent variable is the natural logarithmic value of *Real Hourly Wage*. Without logging, real hourly wage exhibits a positively skewed distribution. Logarithmic transformation preserves the normality of skewed distributions. I computed real hourly wage from the reported nominal hourly rate of pay in dollars (USD) by adjusting for inflation. I used the US consumer price index (CPI) deflator, with 2016 as the baseline.

Independent Variables. *Degree Type* is a time-invariant dichotomous variable coded as "1" if a respondent graduated with an IT degree; "0" if respondent graduated with a non-IT degree including physical science and

mathematics, and (non-computer) engineering. The NLSY97 identifies fields of study using the 2000 Classification Instruction Programs (CIP) taxonomy. The National Center of Education Statistics (NCES) developed the CIP taxonomy to standardize the programs and courses offered by educational institutions in the US. The first two-digits of the CIP codes define the field of study.

CIP codes for IT fields of study begin with “11”, “14” and “52”. IT degrees include computer and information sciences (CIP: 11.0101); information technology (CIP:11.0103), computer programming (11.0201), computer information systems (CIP:11.0401), computer systems analysis (CIP:11.0501), computer and software engineering (CIP:14.09) and business and management information systems and data processing (CIP:52.12).

IT Tenure is a time-varying measure of the cumulative number of years a respondent has spent in IT job roles. Consistent with prior research (Slaughter & Ang, 2007), which explores the relationship between human capital attributes and labor market outcomes, I included the squared terms of all tenure-related variables to model the potential nonlinear effect of tenure on wages.

The intensity of IT-usage of industry is a dichotomous measure (“1” = High Technology Industry; “0” = Low Technology Industry). I identified industries using the US Census’ Standard Industrial Classification (SIC) codes. I categorized industries into high and low technology types by following the approach of Mithas and Krishnan (2008). High technology industries include *Manufacturing, Infocomm, Finance* and *Healthcare* industries. Low technology industries include *Retail and Trade, Services* and other industries.

Table 2: Variable Description and Definition

Variable	Definition
Dependent Variable	
Real Hourly Wage	Log value of the real hourly rate of pay (USD)
Control Variables	
Socioeconomic Status	Log value of the real annual household income of respondent.
Ethnicity: White; Others	Respondent's ethnic affiliation. Others is the reference category.
Sex: Male	Biological classification of respondent as male; female is the reference category.
College Type: Private College	College attended is publicly funded; reference category is public college.
Education Level: Bachelor's Degree; Associate's Degree	Level of education attained; reference category is Associate's Degree.
Academic Performance	Log value of the respondent's GPA
Cognitive Ability	Log value of respondent's ASVAB score.
Firm Mobility	Individual movement across firms coded as "1" if a respondent exits an incumbent firm; and "0" if a respondent stays with the firm.
Working Hours	Log value of the weekly working hours.
Firm Size	Log value of the total number of employees in a firm.
Independent Variables	
Degree Type: IT degree; Non-IT degree	Whether respondent attained an IT degree; Non-IT degree is the reference category.
Intensity of IT usage of Industry: High Technology Industry; Low Technology Industry	Measure of intensity of IT usage of industry. Categorized based Standard Industry Classification codes; reference category is Low Technology Industry.
IT Tenure; IT Tenure (squared)	The cumulative number of years spent in IT job roles.

Control Variables. Consistent with prior research, I included a series of control variables theorized to influence the wages of IT professionals. I controlled for *Cognitive Ability* and *Academic Performance*. Cognitive ability is a time-invariant score of the Armed Services Vocational Aptitude Battery (ASVAB). The NLSY97 administers a computer adaptive version of the ASVAB to respondents. The ASVAB tests measure the aptitude of respondents in topical areas including general science, arithmetic reasoning, coding speed, mechanical comprehension and work knowledge.

Academic performance is a measure of the final grade point average (GPA) of respondents. GPA is measured on a standardized 4.0 scale. Both measures of cognitive abilities and academic performance are logged to enable an easier interpretation of the results.

Education Level is a dichotomous variable coded as “1” if a respondent attained a bachelor’s degree; “0” if a respondent attained an associate’s degree. *College Type* is a dichotomous variable coded as “1” if a respondent graduated from a private college; “0” if a respondent graduated from a public college.

Prior research has demonstrated that IT professionals move to new firms to receive higher wages (Joseph et al., 2012). Accordingly, I controlled for firm mobility. *Firm Mobility* is a dichotomous variable (“1” = if respondent exits an incumbent firm; “0” = if respondent stays with the incumbent firm).

Prior research has found that larger firms pay higher IT wages (Ang, Slaughter, & Yee Ng, 2002). Consistent with this finding, I controlled for the

effect of *Firm Size*. Firm size is a measure of the number of employees in the incumbent firm.

It is conceivable to argue that high paying jobs have longer working hours. Accordingly, I controlled for *Working Hours*. Working hours is a measure of the reported weekly working hours.

I accounted for the potential effects of demography and sex on wages. I coded for ethnicity coded as “1” if a respondent is of white ethnicity; Other ethnicities are coded as “0”. *Sex* is a dichotomous variable (“1” = Male; “0” = Female). *Socioeconomic Status* is a measure of the annual household income of a respondent. Household income is adjusted for inflation using the CPI deflator with 2016 as the baseline year.

Data Analytical Approach

I analyzed the data using a linear mixed effects modelling technique. A linear mixed effects model is an extension of the linear regression models. It affords the researcher the flexibility to incorporate both fixed and random effects.

Linear mixed effects modelling is particularly suitable for the current analysis for the following reasons. First, mixed effects modelling accounts for the presence of groups or panel observations (Nezlek, 2001, 2008), which causes observations to be dependent as in the case of the current study. Failure to account for this dependency in the estimation of the model would produce inconsistent regression estimates and standard errors.

Mixed effects modelling affords considerable flexibility in that it simultaneously specifies and estimates within- and between-group residual error terms. This excises away bias caused by the dependent observations (Bliese & Ployhart, 2002).

Second, mixed effects model employs the versatile maximum likelihood (ML) estimation technique, which maximizes the likelihood function that models the parameters of the observed sample (Garson, 2012). ML estimation technique therefore produces the precise estimates of the observed data (Garson, 2012).

To test the hypotheses, I specified four models in incremental steps. I specified both random and fixed effects for all the four models. The intercept is specified as random to vary across individuals and all the predictors are specified as fixed effects. The specification of the intercept as random effect acknowledges the individual heterogeneity in wages.

Model I, is the null model and contains no predictors. Model II tests hypothesis 1 by estimating the main effect of *Degree Type* on *Real Hourly Wage*. Model III tests hypothesis 2 by estimating the effect of IT tenure on the relationship between *Degree Type* and *Real Hourly Wage*. Model IV tests hypothesis 2 by estimating the effect of *IT Degrees* on *Real Hourly Wage* across the *High* and *Low Technology* industries. The *Real Hourly Wage* of each observation *i* for individual *j* is modeled as a linear function of the predictor and control variables in equation 1.

$$\begin{aligned}
RealHourlyWage_{ij} = & \beta_0 + \beta_1 SocioeconomicStatus_{ij} + \beta_2 Ethnicity_{ij} + \beta_3 Sex_{ij} + \\
& \beta_4 CollegeType_{ij} + \beta_5 EducationLevel_{ij} + \beta_6 AcademicPerformance_{ij} + \\
& \beta_7 CognitiveAbility_{ij} + \beta_8 FirmMobility_{ij} + \beta_9 WorkingHours_{ij} + \beta_{10} FirmSize_{ij} + \\
& \beta_{11} DegreeType_{ij} + \beta_{12} ITTenure_{ij} + \beta_{13} ITTenure_{ij}^2 + \\
& + \beta_{14} IntensityOfITUsageOfIndustry_{ij} + u_j + r_{ij};
\end{aligned}$$

where u_j and r_{ij} denote the between-subject (or panel) and within-subject residual terms.

Results

The descriptive statistics and correlations are shown in Table 3. Table 4 presents the results of the linear mixed effects model. The estimates are the unstandardized regression coefficients and carry the same interpretation of OLS regressions. Hypothesis 1 predicted that IT degrees command higher wages than non-IT degrees in early IT careers. Results of Model II from Table 4 indicate that the relationship between IT degrees (with non-IT degrees as reference category) and real hourly wage is positive and significant ($\beta = 0.156$; t value = 2.693, $p < 0.05$).

Therefore, I find support for Hypothesis 1. IT degree holders earn \$1.168 per hour more than non-IT degree holders ($\Delta Real Hourly Wage = \text{antilog}(0.155) = \1.169). To provide an easier interpretation, I computed the difference in the accrued wages of IT degree and non-IT degree holders based on a 35-hour work week for 52 weeks (per annum). IT degrees yield an annual return of \$2,128 more than non-IT degrees in early IT careers.

Table 3: Descriptive Statistics and Correlations

		Mean	SD	1	2	3	4	5	6
1	Real Hourly Pay	2.766	0.638						
2	Socioeconomic Status	11.053	0.919	0.014					
3	Ethnicity: White	0.648	0.478	0.041*	0.124**				
4	Sex: Male	0.723	0.448	0.057**	0.038*	0.074**			
5	College Type: Private	0.395	0.489	-0.003	0.106**	-0.193**	-0.119**		
6	Education Level: Bachelor's Degree	0.557	0.443	0.019	0.047*	0.059**	-0.102**	-0.062*	
7	Academic Performance	1.096	0.320	0.050*	0.039	0.247**	0.070**	-0.016	-0.004
8	Cognitive Ability	10.915	0.653	0.069**	0.106**	0.439**	0.050**	0.019	0.295**
10	Firm Mobility	0.204	0.403	0.022	-0.028	-0.032	0.004	-0.041	0.066*
11	Working Hours	3.700	0.160	0.100**	0.026	0.150**	0.040*	0.033	0.049*
15	Firm Size	2.925	3.957	0.024	-0.006	0.009	0.012	-0.063	0.024
16	Degree Type: IT Degree	0.391	0.486	0.056**	0.003	-0.017	0.290**	-0.088**	-0.077**
17	IT Tenure	3.108	2.488	0.122**	-0.023	0.050**	0.111**	-0.012	0.054*
18	Intensity of IT Usage: High Tech Industry	0.250	0.433	0.029	0.026	0.045*	0.059**	-0.083*	-0.112**

SD denotes standard deviation; * $p < 0.05$; ** $p < 0.01$; $p < 0.001$

Table 3: Descriptive Statistics and Correlations (continued)

	7	8	9	10	11	12	13
1 Real Hourly Pay							
2 Socioeconomic Status							
3 Ethnicity: White							
4 Sex: Male							
5 College Type: Private							
6 Education Level: Bachelor's Degree							
7 Academic Performance							
8 Cognitive Ability	0.342***						
9 Firm Mobility	0.021	-0.048*					
10 Working Hours	0.023	0.139**	-0.027				
11 Firm Size	0.002	-0.003	0.022	-0.003			
12 Degree Type: IT Degree	0.142**	0.020	-0.040	0.015	0.045		
13 IT Tenure	0.111*	0.141**	-0.053*	0.075**	0.050*	0.276**	
14 Intensity of IT Usage: High Tech Industry	0.115**	-0.013	-0.033	0.030	0.035	0.084**	0.092**

* $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 4: Results of the Mixed Effects Model

	Real Hourly Rate											
	Model I			Model II			Model III			Model IV		
	Estimate	se	t value	Estimate	se	t value	Estimate	se	t value	Estimate	se	t value
Intercept	2.760***	0.022	123.7	1.635*	0.734	2.227	2.571*	1.211	2.123	1.207*	0.546	2.211
Socioeconomic Status				-0.026	0.018	-1.478	-0.064	0.044	-1.452	-0.004	0.095	-0.042
Ethnicity: White				0.044*	0.018	2.498	0.042	0.051	0.822	0.067	0.040	1.675
Sex: Male				-0.028	0.071	-0.392	-0.023	0.037	-0.629	-0.012	0.026	-0.457
College Type: Private				0.057	0.064	0.891	-0.094	0.288	-0.326	-0.034	0.105	-0.324
Education Level: Bachelor's Degree				0.355***	0.084	4.211	0.423***	0.108	3.923	0.324***	0.087	3.738
Academic Performance				0.155	0.271	0.573	0.136	0.610	0.223	0.126	0.103	1.222
Cognitive Ability				0.071*	0.033	2.122	0.054	0.127	0.425	0.093	0.149	0.624
Firm Mobility				0.067*	0.030	2.232	0.097	0.056	1.736	0.077*	0.035	2.214
Working Hours				0.082*	0.041	1.993	0.036	0.021	1.721	0.035	0.212	0.165
Degree Type: IT Degree	H1			0.156**	0.065	2.693	0.133*	0.061	2.165	0.112*	0.050	2.238
IT Tenure							0.099***	0.031	3.218	0.116**	0.046	2.525
IT Tenure (squared)							-0.004***	0.001	-3.424			
Degree Type X IT Tenure							0.049	0.355	0.138			
Degree Type X IT Tenure (squared)	H2						0.052*	0.023	2.222			
Firm Size										-0.014	0.025	-0.559
Intensity of IT Usage of Industry										-0.155	0.141	-1.101
IT Degree X Intensity of IT Usage of Industry	H3									0.450*	0.201	2.234
Deviance (-2 Log Likelihood)	4802			2629.531			2598.414			2529.539		
Pseudo R-Squared				0.331			0.434			0.489		

* $p < 0.05$; ** $p < 0.01$; $p < 0.001$

Hypothesis 2 predicted that the growth rate of wages engendered by IT degrees is higher than non-IT degree as tenure in IT increases. Results from Model III of Table 4 indicate a positive interaction effect of degree type and IT tenure on wages ($\beta = 0.052$ t value = 2.234, $p < 0.05$). Figure 2 presents the graph of the interaction effect.

IT degree holders accrue \$1.053 per hour more than non-IT degree holders as IT tenure increases from 0 to 5 years ($\Delta \text{Real Hourly Wage} = \text{antilog}(0.052) = \1.053). Figure 2 shows that the significant difference in wages is observed from the beginning of the second year in early IT careers through to the fifth year. Hypothesis 2 is therefore supported.

Figure 2: Degree Type and Wage Growth

Hypothesis 3 predicted that the high technology industry pays higher wages than the low technology industry for IT degree credentials. Results of Model IV from Table 4 indicate that the effect of industry type on the relationship between IT degree and real hourly wage is positive and significant ($\beta = 0.450$, t value = 2.185, $p < 0.05$). Figure 3 graphs the interaction effect.

The high technology industry pays \$1.568 per hour more than the low technology industry for IT degrees (Δ Real Hourly Wage = $\text{antilog}(0.450) = \1.568). Annually, employers in the high technology industry pay \$2854 more than employers in the low technology industry for IT degrees. Hypothesis 3 is therefore supported.

Figure 3: Intensity of IT Usage Industry and Wages

Robustness Check

Self-selection or endogenous bias threatens the validity of observational studies that estimate the average effect of a “treatment” on an outcome variable of interest (Antonakis, Bendahan, Jacquart, & Lalive, 2014; Dehejia & Wahba, 2002). Endogenous selection refers to the nonrandom selection of subjects into groups based on observed and unobserved characteristics (Austin, 2011).

In the case of the current study, the effect of IT degrees, compared with non-IT degrees, on wages is analogous to a treatment effect. IT graduates are the treatment group and non-IT graduates are the nonexperimental comparison (or “untreated”) group. IT labor market is not the traditional labor market for non-IT graduates. It is therefore conceivable to argue that non-IT graduates who enter the IT labor market anticipate receiving higher economic returns than they would in their respective traditional labor markets. Consequently, the observed wages of non-IT graduates in the sample may be higher than the average wage of the whole sample. Failure to account for the endogenous selection of non-IT graduates could result in inconsistent estimates.

To address the concerns of possible bias caused by endogenous selection of non-IT graduates into the IT labor market, I conducted a robustness check using propensity score matching analysis (Rosenbaum & Rubin, 1983). Propensity score matching analysis is a statistical technique that matches subjects from a treated group with subjects from an untreated group based on the similarity of their propensity scores. The average treatment effect of the treated is estimated using the matched sample (Caliendo & Kopeinig, 2008;

Rosenbaum & Rubin, 1983). Appendix I presents details of the propensity score matching analysis. The results of the propensity score matching analysis is consistent with our initial results.

Discussion

The current research set out to achieve three goals. First, I draw largely on the literatures on human capital specificity (Becker, 1975) and occupational matching (Hersch, 1991; Sattinger, 1993) to examine the value of IT oriented degrees relative to non-IT degrees. Second, I examine the growth rate of wages of IT professionals who hold IT degree credentials relative non-IT degree credentials. Third, I draw on the literatures on human capital specificity and core competency theory (Hamel & Heene, 1994) and examine the value of IT degrees, compared with non-IT degrees, in the high and low technology industries.

The Value of IT and Non-IT Degrees

Consistent with the literatures on human capital specificity (Becker, 1975) and occupational matching (Hersch, 1991; Sattinger, 1993), the results indicate a greater valuation for IT degrees than non-IT degrees. A match between an individual's stock of occupation-specific human capital and the occupation he or she enters results in the effective and productive utilization of human capital (Hersch, 1991).

Conversely, a mismatch imposes a productivity ceiling that limits the utilization of occupation-specific human capital (Hersch, 1991). The disparity

in the levels of productivity prompted by the human capital-occupation mismatch would have wage implications (Becker, 1975).

On-the-job training for newcomers could contribute to the disparity in wages of IT and non-IT degree holders. Employers incur both out-of-pocket and opportunity costs in upskilling newcomers (Carless & Arnup, 2011; Joseph et al., 2015). The differences in the level of accumulated IT human capital between IT and non-IT degree holders result in a relatively higher cost for upskilling non-IT degree holders. To recoup the cost, IT employers may pay lesser wages to non-IT degree holders.

Wage Growth of IT and Non-IT Degrees

There is differential growth in the wages of IT and non-IT degree holders in early IT careers. Specifically, the difference in the valuation of IT and non-IT degrees is observed from the second to the fifth year in early IT careers. This finding could be attributed to the differences in the learning capabilities of IT and non-IT degree holders as they encounter new technological challenges.

The first two years of the early career stage is a reasonable timeframe for employers to upskill new entrants via on-the-job training. The training enables new entrants to build firm-specific competencies in IT. But the abilities of new entrants to learn effectively on the job and raise their productivity levels is predicated on their foundational background.

New entrants who hold IT degrees have a strong foundational knowledge in IT. IT professionals who have foundational knowledge in IT have

a higher capacity to assimilate new knowledge and build new competencies (Boh, Slaughter, & Espinosa, 2007), as they gain tenure in IT and encounter new technologies. This capability to assimilate new IT concepts and build new IT skills provides IT degree holders with a learning advantage over non-IT degree holders, which translates to increased productivity and wage growth. The finding and explanations are consistent with the study of Brown (1989) who demonstrated that wage growth occurs after periods of on-the-job training suggesting that “wage growth is mainly determined by contemporaneous productivity growth” (p. 971).

Institutional Pricing of IT Degrees

The finding that IT degrees command higher wages in the high technology industry than the low technology industry is consistent with prior research that have found greater valuation for IT-specific human capital in the information-intensive industry (Ang, Slaughter, & Yee Ng, 2002; Mithas & Krishnan, 2008). Employers in the information-intensive industry regard technical expertise and IT proficiencies as central to their core competency of using sophisticated and cutting edge technology to deliver solutions to their clients (Ang, Slaughter, & Yee Ng, 2002).

Similarly, IT-specific human capital is central to the core operations of firms in the high technology industry. Thus, employers in the high technology industry have a greater need for IT graduates than employers in the low technology industry. Therefore, investments in IT degrees are of greater value

to employers in the high technology industry relative to the low technology industry.

Implications for Research

The findings of the current research have important implications for future research and contribute to the development of new theoretical insights regarding IT human capital. First, the finding that IT degrees have greater valuation than non-IT degrees reconciles the competing thesis concerning the value of IT and non-IT human capital in the IT profession. In addition, the current study broadens our understanding of IT human capital by theorizing that IT degree represents valuable investments in occupation-specific human capital. Prior research tends to narrowly focus on the value of IT experience and firm-specific experience (e.g. Joseph, Ang, & Slaughter, 2006; Mithas & Krishnan, 2008; Slaughter et al., 2007).

This study opens an avenue for future research regarding the value of other forms of IT education credentials. For example, IT professionals in different career stages increasingly pursue IT certification credentials in different aspects of IT as a way of signaling technical competence to prospective employers. Future research should examine the value of IT certification credentials and whether IT certifications complements or substitutes formal IT degrees in determining wages.

Second, the current study complements the literature on the returns to education credentials in the IT profession because the current analysis directly examines the value of IT degrees across a tenure profile, whereas previous

research does not (see Ang, Slaughter, & Yee Ng, 2002; Levina & Xin, 2007; Mithas & Krishnan, 2008). Previous research provides only a snapshot or time-agnostic narrative of the returns to education credentials in the IT profession (e.g. Ang, Slaughter, & Yee Ng, 2002; Levina & Xin, 2007; Mithas & Krishnan, 2008). The finding that IT degrees compared with non-IT degrees increase in value with increasing tenure has the potential to inform and refine temporal theories of IT human capital.

Recall that the difference in the wages engendered by IT and non-IT degrees is observed in the second year of IT tenure. The value of IT degree after the second year is perhaps indicative of the period that the skills gained from IT degrees are productively utilized in early IT careers. Future research should extend this finding by examining the value of IT degrees across longer tenure profiles or the full course of IT careers.

Third, this study is novel in its finding that firms in the high technology firms place greater value on IT degrees than the firms in the low technology industry. The extant IT research has focused attention on how firms in the high and low technology industries discriminate wages based on the levels of firm-specific experience and IT experience (Ang, Slaughter, & Yee Ng, 2002; Bapna et al., 2013; Mithas & Krishnan, 2008).

The theoretical insight that higher levels of firm-specific experience and IT experience are required to move the needle on wages in high technology firms does not adequately explain the heterogeneity in the wages of early career IT professionals. This is because early career IT professionals are not well

endowed with firm-specific experience and IT experience. The current study focuses on early career IT professionals and theorizes that there is greater valuation for IT degree credentials by employers in the high technology industry. This study therefore adds to the extant literature on the pricing of IT human capital at the institutional level.

Implications for Practice

The findings of the current study have important implications for prospective IT graduates, early career IT professionals and IT employers. First, for prospective IT graduates the current study provides evidence that should bring finality to the debate and questions about the value of IT degrees, many of which are based on anecdotes published in the popular press. The current study should aid individuals make informed decisions in regards to educational choices in IT.

Second, for early career IT professionals the findings of the current study provide evidence that could inform early career strategies that maximize returns to IT human capital. IT professionals who have attained formal IT degrees should be aware that firms in the high technology industry pay significantly higher wages than the low technology industry. This should aid IT graduates in making informed career decisions with regards to the choice of industry.

Third, findings of the current study serve as a benchmark for pricing IT human capital and determining the wages of IT and non-IT graduates in IT jobs. Employers in both the high and low technology industry could use the study in

negotiating the wages of early career IT professionals. Further, the findings could inform human resource policies and practices for attracting and retaining early career IT professionals. Wages are an important lever for attracting and retaining IT talents.

Conclusion

The current study takes a three-pronged approach in examining the value of IT degrees. First, I examine the value of IT degrees compared with non-IT degrees in early IT careers. I find that IT degree holders earn \$1.169 per hour more than non-IT degree holders in early IT careers, which translates to an annual difference of \$2128.

Second, I examine the growth value of IT degrees compared with non-IT degrees as tenure increases. I find that there is greater valuation for IT degrees than non-IT degrees as tenure in IT increases.

Third, I examine the value of IT degrees compared with non-IT degrees in the high and low technology industries. I find that IT degree holders earn \$1.568 per hour more in the high technology industry than the low technology industry, which translates to an annual difference of \$2854.

APPENDIX I

Propensity Score Matching Analysis

Propensity score matching evaluates the effect of a treatment by matching treated and untreated observations based on propensity scores (Austin, 2011; Dehejia & Wahba, 2002; Rosenbaum & Rubin, 1983). Propensity score is the conditional probability that an observation receives treatment based on observed time-invariant individual characteristics such as traits (Rosenbaum & Rubin, 1983). Propensity scores are computed using discrete choice regression models with the treatment as the dependent variable and traits as the explanatory variables.

For the current analysis, I argue that analytical abilities and personality traits including conscientiousness and cooperativeness influence an individual's choice of pursuing IT degrees (Lounsbury et al., 2009). College students hold personality and skills-related stereotypes of certain professions (Pringle, DuBose, & Yankey, 2010). Their choice of an academic major may therefore be influenced by the degree to which they believe their personality and aptitude match with that of the profession (Pringle et al., 2010). Prior research indicates that IT professionals differ significantly from other professionals on analytical abilities and traits of conscientiousness and cooperativeness (M. Ahuja, Ogan, Herring, & Robinson, 2006; Lounsbury et al., 2009).

I measure analytical abilities with the Scholastic Aptitude Test (SAT) scores of respondents. SAT is a globally recognized college admission

examination which tests students on quantitative, analytical and verbal abilities. Traits of conscientiousness and cooperativeness are measured with a single item asking respondents how well the traits are applicable to them (“1” = Disagree strongly ... “7” = Agree strongly). The NLSY97 SAT and personality score measures have been validated and used in prior research (Rohrer, Egloff, & Schmukle, 2015).

I estimate the propensity scores, $p(x)$, for observations using the following probit equation:

$p(x) = \text{probability (IT Major} \mid x = \text{SAT, Personality variables)} = E(T \mid x)$. The likelihood that an individual pursues an IT degree given x , is therefore the predicted or expected outcome, E , of receiving “treatment”, T . Results of the probit model are presented in Table 5.

Next, I matched the propensity scores of observations in the “treatment” group, (IT degree) with observations in the “quasi-control” group (non-IT degree) using the nearest neighborhood matching algorithm. The estimator of the nearest neighborhood matching technique is given by the following equation (Caliendo & Kopeinig, 2008): $\min | p(x)_i - p(x)_j |$

The nearest neighbor matching analysis compares the propensity score of each observation, i , in the “treatment” group (IT degree) with the propensity score of each observation, j , in the “control” group (non-IT degree), and matches observations with the closest propensity score (Caliendo & Kopeinig, 2008).

For each matched pair of observations i and j , the i^{th} observation in the IT degree group represents the counterfactual of the corresponding j^{th} observation in the non-IT degree group. This suggests that an IT degree holder would receive the same wages as the corresponding match in the non-IT degree group, had the IT degree holder pursued a non-IT degree. This counterfactual assumption is the basis for estimating the Average Treatment effect on the Treated (ATT) (Austin, 2011; Rosenbaum & Rubin, 1983). ATT is computed as the difference between the average wages, W_1 , of IT degree holders and the average wages, W_0 , of the matched observations from the non-IT degree group (Rosenbaum & Rubin, 1983): $ATT = E(W_1 | p(x), \text{IT Degree}) - E(W_0 | p(x), \text{non-IT Degree})$

The results of the propensity score matching analysis are shown in Table 6. To demonstrate the robustness of the results to other matching algorithms, I included the ATT estimated after using kernel and stratification matching algorithms.

Table 5: Results of the Probit Model

Likelihood of Pursuing IT Degree			
	β	se	z
Intercept	-0.362	0.519	-0.700
Conscientiousness	-0.196*	0.073	-2.680
Cooperativeness	-0.096	0.090	-1.060
SAT Math	0.233*	0.081	2.860
SAT Verbal	0.004	0.064	0.060
Log Likelihood (df = 4)	-233.086*		

* $p < 0.05$

Table 6: Estimates of the ATT

Matching	Treatment	Matched	ATT	se	t
Method	Cases	Cases			value
Nearest	141	154	0.145*	0.060	2.430
Neighborhood					
Kernel	141	200	0.190***	0.052	3.644
Stratification	141	200	0.191***	0.049	3.872

* $p < 0.05$ *** $p < 0.001$; ATT calculations are based on the average ln real hourly wages

CHAPTER 4

Summary and Conclusions

Assessment of Research Question and Aims

The current dissertation examines the broader research question of how career interventions and IT degree attainment enable salient early career outcomes – *initial IT employability*, *IT career persistence* and *IT career success*. In answering the broad research question, I proposed two separate studies.

Study 1 follows a two-step approach by examining the enablers of initial IT employment and thereafter career persistence. The two-step inquiry enabled me to provide a comprehensive analysis of college-to-IT work transition, which the current IT literature has only begun to explore (Joseph, 2008b).

In examining the enablers of initial IT employability, I drew largely on human capital theory (Becker, 1975) and IT literature on skills and competencies, which argue that occupational experience is *sine qua non* for performing IT work (Slaughter et al., 2007). I proposed a model that relates college-based career interventions with initial IT employment.

Specifically, high and low direct experiences gained from college-based career interventions should prompt initial IT employment for reasons related to the arguments of human capital theory. Human capital theory (Becker, 1975) argues that occupational experiences build task- and occupation-specific skills that have positive implications for productivity, resulting in desirable

employment outcomes. Consistent with human capital theory, I found that career interventions, in general, increase likelihood of initial IT employment.

In examining the enablers of IT career persistence, I drew arguments largely from the human capital literature and integrated them with concepts from identity theory. Identity theory provides an account by which career interventions foster salient professional identities.

The activation of salient professional identities trigger attachment behaviors to the profession including career persistence (Callero, 1985; Adler & Adler, 2005). Consistent with the arguments flowing from the human capital literature and identity theory (Callero, 1985; Lipsey, 1978; Moore, 1969), I found that career interventions, in general, prompt increased levels of IT career persistence.

Study 2 comes off the back of increasing concerns regarding the value of IT degrees (Fortune, 2015). Specifically, the line of inquiry seeks to bring greater understanding to the question of what enables early career success in IT, in terms of accrued wages. In answering this question, I frame IT degree education as an important antecedent in differentiating wages of IT professionals.

This line of thinking is motivated largely by the arguments flowing from human capital specificity and occupational matching literature (Allen & Velden, 2001; Hersch, 1991). The underlying argument is that employee productivity is better realized when there is an optimal match between the education type and the occupation entered. I found that a solid college degree

in IT proves valuable relative to non-IT degrees in early IT careers, as demonstrated by the higher wages paid to IT professionals who have attained IT degrees.

Contributions to Research

The inquiry into the enablers of the salient early career outcomes has theoretical implications in terms of complementing and extending prior IT research. Research on IT careers has enriched our understanding of objective career success, career mobility patterns and employability in IT (Ang et al., 2002; Joseph, et al., 2006; Joseph et al., 2012; Mithas & Krishnan, 2008; Reich & Kaarst-Brown, 1999; Young, 2000).

Considered as a whole, the findings of the existing studies position occupation-specific human capital as the paramount antecedent in the nomological network of desirable IT career outcomes (Ang et al., 2002; Joseph et al., 2012; Mithas & Krishnan, 2008). The narrative is that quantitative aspects of occupation specific human capital such as firm and IT experience reflects an IT professional's human capital endowment.

The current dissertation moves away from restricting occupation specific human capital to quantitative attributes including firm and IT experience. I argue that career interventions and formal IT education are crucial in the development of occupation specific human capital. The current dissertation reshapes traditional notions regarding the quantitative structure of IT-specific human capital, to include qualitative aspects such as formal IT education and career interventions.

This is theoretically relevant, as it provides the conceptual flexibility to theorize about IT-human capital within the context of the early stage of IT careers, when IT professionals have limited tenure in IT or quantitative work experience.

In addition, the current dissertation refines our understanding of career mobility in IT by providing a new theoretical lens for explaining why some IT professionals persist in IT careers and why others may not. At the nexus of the many theoretical arguments explicating IT career mobility is the view that an IT professional's decision to voluntarily leave or continue to pursue a career in IT is ultimately determined by his or her level of commitment or attachment toward the profession (Joseph, Ang, & Slaughter, 2015c; Ramos & Joia, 2013). An individual's decision to pursue formal IT education is perhaps the most apparent indication of a future commitment to an IT career.

However, the findings of the current dissertation have shown that even for a restricted sample of IT graduates, persistence in IT careers is determined by career intervention experience, *ceteris paribus*. Notably, this finding is novel considering that prior research tends to associate career intervention experience with proximal outcomes including career-relevant skills development (Narayanan et al., 2010).

The current dissertation has demonstrated that career interventions have distal positive effects on persistence in early IT careers. IT researchers should therefore consider the mechanisms of constructing professional identities as

crucial antecedents to turnaway, especially when analyzing samples of early career IT professionals.

Contributions to Practice

The studies presented in the current dissertation hold important implications for prospective IT graduates and IT professionals, institutions of higher learning (IHL) and policymakers. The findings of the current dissertation points to a greater valuation of a solid education in IT fields. Prospective IT talents deliberating on pursuing a college degree in IT as opposed to a nontraditional path to IT can rely on the findings of the current dissertation to make informed career decisions that may yield favorable employment outcomes.

Similarly, for IT professionals the findings and results presented in this dissertation could inform career strategies that lead to tangible market rewards or career success, in terms of accrued wages. The significant difference in industrial pricing of IT degrees vis-à-vis non-IT degrees, has implications for how IT professionals could make career moves across industries. As industries move toward digitization, the educational background of IT professionals will play an important role in determining wages.

Further, IT prospects enroll into computer science and IT degree programs to acquire occupation-specific skills in preparation for a career in IT or to facilitate entry into the IT workforce. The expectation that a college education in IT is pivotal for the development and production of skilled IT labor enjoins IHLs to adequately prepare graduates for the labor market. In this view,

the findings of the current dissertation affirm the need to restructure IT curricula to incorporate sustained periods of vocational training. Essentially, the current dissertation makes a strong case for incorporating in-curriculum career interventions, in line with the evidence that career intervention experiences are associated increased levels of employability.

The results of the current dissertation also have implications for how colleges craft career services programs intended to raise job placement rates. Colleges that institute career interventions are likely to raise the job placement rates of their IT graduates. This in turn could increase the marketability of college IT departments and raise IT enrollment rates.

For policymakers, the current research offer a glimpse into how IT talents could be cultivated and sustained. As highlighted earlier, attrition in early IT careers is of serious concern to both policymakers and government agencies alike. Government agencies and policymakers who have oversight of the production outputs of IHLs could benefit from the findings of the current research in mitigating IT attrition and ensuring a sustainable flow of IT talents to meet current and future demands of digital economies.

Limitations

Exploring the enablers of subjective career outcomes of early career IT professionals is an important extension of the current research, which examines objective career outcomes. Subjective career outcomes refer to psychological outcomes triggered by work-related experiences, whereas objective career outcomes are behavior, actions or measurable achievements that are triggered

by work-related experiences (Hall, 2004). Considering the conceptual distinction between subjective and objective career outcomes, it is reasonable to expect an underlying distinction between their enablers. How early career IT professionals ascribe meaning and success to their careers may be fundamentally different from mid-to-late IT professionals. What drives such differences is theoretically relevant in building a processual narrative of how IT professionals construct and appraise career outcomes over a lifetime.

An important limitation of the current dissertation concerns generalizability constraints resulting from the geographic location of the samples used. The study draws on the NLSY97, which surveys young Americans entering the US labor force. The dynamics of the labor market in the US may present challenges in extending the findings of the current dissertation to other labor markets.

The US economy is perhaps the most digitized, consisting of large technology clusters including the Bay Area, Boston and New York. The pervasive digitization continues to create a high demand for IT manpower than there is supply. This tight labor market condition has implications, not just for IT employers, but also for IT professionals.

A tight labor market shifts the balance of bargaining power to workers. IT professionals in such jurisdictions may experience favorable career outcomes including wage growths and higher employability, which the current dissertation explores. In addition, a tight labor market could impact career

mobility and in effect levels of career persistence as it gives more leverage to IT professionals to explore other career options.

The results of the current dissertation should therefore be interpreted within the ambits of the US IT labor market and other tight labor markets alike. Future replications of the studies that make up the current dissertation could draw samples from slack labor markets to provide a comparison and contrast of the current findings.

Conclusion

A successful digital economy thrives on the sustainable flow of IT talents into IT careers. Yet, research that explores the enablers of salient early career outcomes of IT professionals that are pertinent to the sustainability of digital economies remain scarce. Accordingly, the current dissertation aimed to fill this gap in the literature by examining the relationship between *career intervention experience* and *initial IT employment* and *IT career persistence*. Further, I examined the relationship between *occupation-specific education* and *early career success*, in terms of accrued wages.

The results indicate that career interventions including cooperative education, internship and mentorship facilitate initial IT employment. In addition, internship and mentorship experiences are associated with increased levels of career persistence. In general, I find that the attainment of a college IT degree, as opposed to a non-IT degree is associated with wage premiums in the IT labor market.

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